The Integration of AI in HRM and the effects on Innovation Outcomes

Master Thesis Report

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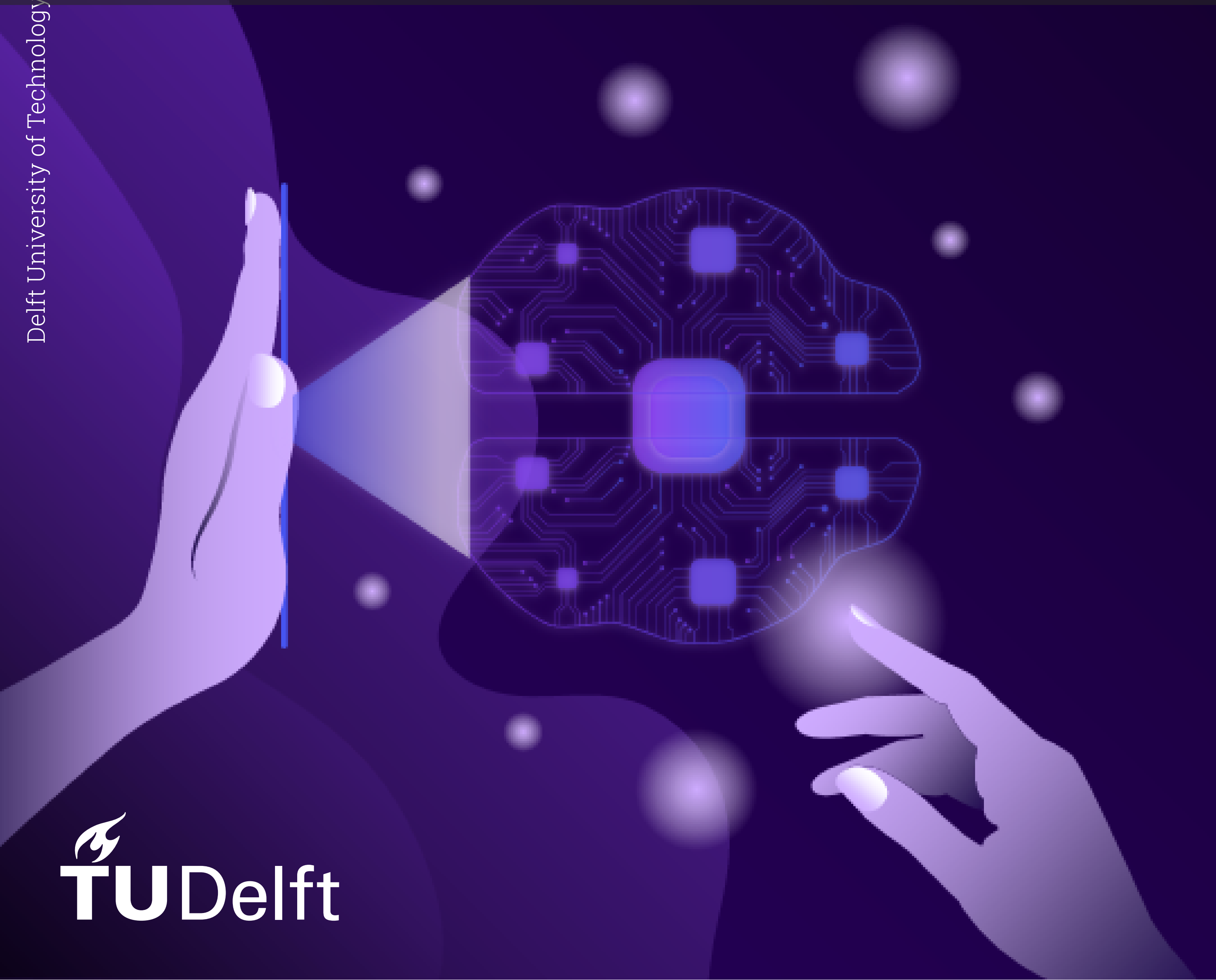

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by

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Preface

Two years ago, I made one of the most significant decisions of my life leaving my full-time job to pursue a master's degree in an entirely new country. This bold move marked the beginning of an incredible journey filled with both challenges and rewarding experiences. The transition from working full time to becoming a full time student was quite challenging. Adjusting back to the rhythm of academic life after years of professional experience felt unusual at first. This period has been enriching providing me not only with academic knowledge but also life skills such as resilience, adaptability and determination.

Throughout this journey I was fortunate to have the guidance of my thesis committee. First of all I would like to thank Robert Verburg for being the chair of my thesis committee . His insightful feedbacks during meetings greatly helped to realign my thesis. I would like thank Dr Nikos Pachos-Fokialis, for being my first supervisor and mentor during my thesis. He helped me greatly from the start of the thesis till its end and even helped me with my silly doubts. His constructive feedbacks and insights helped me a lot. I also thank Dr Martin Sand for being my second supervisor. I am grateful for all the feedback he gave during thesis meetings and helping me create a cohesive research. Finally, I would like to thanks all the participants who took part in the interview for my thesis.

I am immensely grateful to my family who have supported me every step of the way. Your encouragement has been my greatest strength throughout this remarkable journey. Finally a big thanks to all my friends present here and scattered across different time zones who supported me through the fun times and not so fun times resulting in great memories.

Reflecting on this journey, I am convinced that taking this leap of faith was the right decision. Despite the ups and downs, this experience has provided me growth and a deeper understanding of my goals and passions.

Omkar Ashish Nayak
Delft, June 2025

Executive Summary

This thesis investigates the integration of Artificial Intelligence (AI) into Human Resource Management (HRM) practices and its resulting impact on innovation at both the individual and organizational levels. As AI continues to transform business functions HRM is increasingly adopting AI-driven tools across recruitment, training, performance management and talent development. HRM which was once seen as a primarily administrative role is now undergoing a significant transformation to strategic partner in fostering innovation.

Academic research has explored AI applications in various business domains including HRM. Studies have examined AI's role in automating tasks, personalizing learning and enhancing analytics. Others have looked at AI's influence on employee engagement, decision support and productivity. But the intersection between AI-integrated HRM and innovation outcomes remains underexplored in current literature. This research seeks to fill this gap by employing a systematic literature review of 42 peer-reviewed articles and the findings through interviews with HR professionals in high-tech industries.

The study proposes a two-level analysis individual and organizational which illustrates how AI-integrated HRM can enhance innovation through improved capability development, motivational pathways and opportunity creation. Findings from the interviews revealed that while participants were initially unfamiliar with the direct relationship between AI in HRM and innovation but they acknowledged the potential after being introduced to the concept. They also identified several benefits such as increased employee autonomy, better talent allocation and improved agility. They also discussed challenges such as data quality issues, algorithmic bias and employee resistance to AI adoption. But they stressed the need for human oversight, transparent communication and a cultural shift in how AI is introduced and managed within HRM.

This study contributes to existing literature by offering practical insights into how organizations can leverage AI in HRM to drive innovation. It highlights the need for strategic alignment between AI tools and HR objectives as well as the importance of trust, explainability and employee involvement in AI-driven processes.

Overall, the research offers a roadmap for companies aiming to integrate AI in HRM while creating a sustainable culture of innovation.

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Nomenclature

Abbreviation	Full Form
AI	Artificial Intelligence
HRM	Human Resource Management
AI-HRM	AI-integrated Human Resource Management
IWB	Innovative Work Behaviour
EDI	Employee-Driven Innovation
AMO	Ability, Motivation, Opportunity framework
XAI	Explainable Artificial Intelligence
ML	Machine Learning
SLR	Systematic Literature Review
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
KPI	Key Performance Indicator
SME	Small and Medium-sized Enterprises
MNE	Multinational Enterprise
R&D	Research and Development
HPWS	High performance work systems
HC	Human Capital
SC	Social Capital
NLP	Natural language processing
HR	Human Resources
PM	Performance Management
T&D	Training and Development
SOE	State Owned Enterprises
ATS	Application Tracking System
VR/AR	Virtual Reality/ Artificial Reality
FMCG	Fast-Moving Consumer Goods
HREC	Human Research and Ethics Committee
LMS	Learning Management System
RPA	Robotic Process Automation
HRIS	Human Resource Information Systems
GDPR	General Data Protection Regulation

1
Introduction

Artificial Intelligence (AI) over the past decade has transformed from a theoretical concept into one of the most powerful drivers of the industrial revolution 4.0. AI started its life from research labs and speculative fiction and now it is a crucial component of everyday life powering voice assistants, recommendation systems, autonomous vehicles and complex data-driven decision-making tools. This rapid evolution was brought by advances in machine learning, neural networks and vast data availability. It positioned AI as a central force in reshaping how societies function and how industries operate. Additionally, AI is not only automating repetitive tasks but also improving and supporting human capabilities by providing real time analytics resulting in smarter and faster decisions across sectors. As AI systems become more integrated in organizations they are redefining the boundaries of human and machine collaboration.

Human Resource Management (HRM) is one such function where AI is now being integrated into. This has become one of the most transformative shifts in contemporary organizational management. Traditionally HRM has functioned as an essential but largely administrative arm of business organizations. The shift from traditional to AI-enabled HRM practices signifies a transformation in how organizations attract, develop and retain talent (Varma et al., 2023). Machine learning algorithms, chatbots, predictive analytics and other AI tools are being employed for recruitment, performance management, training and employee engagement (Huang and Rust, 2018; Charlwood and Guenole, 2022). These technological enhancements not only improve HR efficiency but also influence innovative behavior by personalizing employee experiences which optimizes workflows and providing data driven decision making (Jatobá et al., 2023).

Innovation is widely recognized as a critical driver of organizational success and competitiveness in the knowledge economy (Chowhan, 2016). It is also inherently tied to human ingenuity, collective intelligence and dynamic capability development (Veenendaal, 2015; Bos-Nehles and Veenendaal, 2019). With the integration of AI in HRM systems it brings an important question what effect does this integration have on the innovative capabilities. This further highlights the AI's capability on one hand to optimize efficiency and decision-making and its potential to dehumanize work and disturb autonomous thought on the other. Noting that innovation and Human Resource functions are human centric (Seeck and Diehl, 2017; Lin and Sanders, 2017). Given all the discussion about AI, HRM and innovation there has not been any research on the effects of AI integration in HRM in terms of innovation which as discussed above is quite crucial for organizations to succeed.

Some organizations experience increased agility, creativity and knowledge sharing while others struggle with implementation barriers, ethical dilemmas and employee resistance (Wikhamn et al., 2023). This study is motivated by the need to understand these complexities and contribute empirically grounded insights to both theory and practice.

1.1. Context of Research

As mentioned above that innovation is inherently a human-centered process which relies on creativity, collaboration and knowledge sharing (Seeck and Diehl, 2017; Lin and Sanders, 2017). HRM practices have long been recognized as enablers of innovation through mechanisms such as training, performance management and participative work design (Laursen & Foss, 2003). However as AI systems begin to augment or replace these practices their influence on innovation needs to be critically examined.

The current literature offers valuable but partial perspectives on the relationship between HRM, AI and innovation. While there have been a lot of studies conducted to see how AI can be implemented in HRM and various algorithms have been also developed to make HRM a formidable strategic partner in an organization growth and development but what impact it has on the innovation outcome is scarce. Some connections can be made from combining existing literature that AI-enabled HRM can foster innovation by enabling personalized learning (Gong et al., 2025), automating routine tasks to free cognitive resources (Marvi et al., 2024) and supporting evidence-based decisions. AI-driven talent analytics can help organizations identify and support innovative potential within their workforce (Chowdhury et al., 2023).But also highlights some challenges such as algorithmic bias, transparency and ethical concerns (Charlwood and Guenole, 2022; Marvi et al., 2024). Additionally, it can also result in loss of human judgment, erosion of employee trust and opacity in decision-making processes (Varma et al., 2023).

This thesis aims to explore deep into what are the actual effects of AI integrated HRM in terms of innovative impact. The study will conduct an extensive literature review and try to establish detailed theoretical connections between AI HRM and innovative outcomes. So, we have modeled this thesis as a literature review research with additional insights from real world where we will be conducting an extensive literature review and interviews with HRM managers from organizations to add on to our findings. Additionally, the literature review will be conducted using a two-level analytical approach: individual-level and organizational-level innovation effects.

1.2. Research Questions

As this study is trying to explore the impact of Artificial Intelligence (AI) being integrated into Human Resource Management (HRM) and its impact on Innovative outcomes.

The main research question that will help us address this is :

How does the integration of AI in HRM practices impact innovative outcomes?

1.2.1. Sub research questions:

These sub questions will help deconstruct the broad research agenda into manageable studies which will allow us to systematically explore the mechanisms through which AI in HRM affects innovation, the barriers encountered and the specific technologies in use. These sub questions are also designed as way to systematically guide us through the research.

1. **How AI is integrated into the HRM practices?**

   This sub research question is selected to explore the practical and technical dimensions of AI implementation within HRM functions. Understanding how AI is integrated into core HRM practices provides essential context for analyzing its potential effects on innovation. This foundation is critical for assessing the relevance and impact of AI integrated HRM on individual and organizational innovation outcomes.

2. **What tools are being used as part of the AI integration in HRM?**

   This question has been chosen as it will help us map the current AI landscape in HRM such as AI-powered recruitment platforms, sentiment analysis engines, learning algorithms and predictive workforce analytics (Black and van Esch, 2020; Pan and Froese, 2023). This will lay the groundwork for us to study how these will impact the innovation outcomes.

3. **How implementation of AI in HRM leads to individual and organisational innovation outcomes?**

   This subresearch question is central to understanding the impact of AI driven HRM. It focuses on exploring how the integration of AI technologies in HR practices contributes to fostering innovation at both the individual and organizational levels. It adds on to the existing knowledge from HRM literature and evaluates how AI modifies or strengthens known pathways to innovation within the workforce and the organization.

2

Theorectical Background

In this section we will explore how Human resource management(HRM) support innovation and what are its innovation outcomes and then we will delve into how Artificial Intelligence (AI) is integrated in HRM. We will also explore the challenges faced when aligning HRM with innovation needs and challenges when integrating AI in HRM systems. After this detailed analysis we draw what are the innovative outcomes of AI - HRM integration in the results and discussion section. The theme table for the literature review can be found in Appendix A.

2.1. Innovation and HRM

HRM plays a pivotal role in fostering innovation through its core functions. It requires strategic alignment not only to shape a capable workforce but also to cultivate an environment that supports and empowers innovative behavior and outcomes.

In this section we will explore what and how HRM supports innovation through its functions. Here we will use the same four categories that we creation the previous section.

2.1.1. Recruitment and Selection

Recruitment and selection processes directly influence a firm's innovative capacity by shaping the knowledge, skills and attitudes of current and incoming employees. By targeting candidates with diverse cognitive backgrounds, collaboration skills and a will to learn the organizations can build human and social capital that supports innovation (Bornay-Barrachina et al., 2017). This section outlines how effective recruitment and selection practices lead to innovative outcomes by enhancing cognitive diversity, enabling knowledge flows and strengthening innovation-supportive employment relationships.

Innovative Behavior through Cognitive Diversity

Recruiting supports innovation when they look for cognitive diversity which is the difference in how individuals think, solve problems and interpret information. Employees who offer diverse perspectives, domain experiences and mental models contribute to a better idea generation and unconventional problem solving. Veenendaal (2015) highlights that diversity fuels creative capital which is the foundation for novel thinking and innovative work behavior (IWB). Hiring individuals with “T-shaped” skill profiles which is explained as deep expertise in one area combined with the ability to collaborate across disciplines enhances cross-functional integration and idea recombination both of which are crucial for product and process innovation.

This cognitive diversity directly correlates with enhanced innovative outcomes such frequent ideation, higher originality of suggestions and broader exploration of alternatives. Hong et al. (2019) noted that when organizations bring in talent with diverse educational or industry backgrounds they often report increased levels of idea generation and greater variety in solutions during innovation projects.

Knowledge Transfer and Cross-Functional Innovation

Lindblom and Martins (2022) note that selecting candidates who facilitate knowledge transfer across functions particularly between R&D and customer facing units directly contribute to complex innovation initiatives. These hires provide a smooth cross-functional collaboration which helps to bridge the gap that hinder information flow. Innovative outcomes of this strategy include faster go-to-market timelines for new products and enhanced responsiveness in customer-driven innovation efforts.

Lindblom and Martins (2022) also noted that manufacturing firms that intentionally recruit individuals with both technical depth and market facing experience report improved alignment between technological potential and market needs which leads to commercially viable innovations that are both novel and user centric.

Organizational Innovation Strategy

Chowhan (2016) links innovation performance to the strategic alignment between HR practices and organizational innovation goals. The studies discusses that firms experience stronger performance in product development and process improvement when recruitment and selection are tailored to attract individuals who fit an innovation focused strategy that is who are flexible, forward thinking and risk tolerant. This alignment ensures that the talent pool not only meets current technical needs but also advances the firm’s adaptive capacity in dynamic markets.

Similarly Bornay-Barrachina et al. (2017) demonstrate that mutual investment employment relationships where both employer and employee commit to long term value creation encourages innovative behaviors such as idea sharing and joint problem solving. Thus strategic recruitment contributes to creating a psychologically safe climate where innovation can flourish.

Collaborative Innovation

As firms move toward innovation centric models recruitment must prioritize individuals with a strong external orientation that is candidates are comfortable collaborating across organizational boundaries and bringing in outside ideas. Hong et al. (2019) argue that teamwork based recruitment which emphasizes openness and collaborative mindsets reduces the cognitive and transactional barriers to innovation. The result is greater participation in co-innovation initiatives with partners such as universities, startups and customers. Innovative outcomes associated with this practice include the successful absorption of external knowledge, increased frequency of inbound idea contributions and more effective joint ventures and R&D partnerships (Naqshbandi et al., 2023). Organizations that recruit employees who have previously engaged in cross boundary collaboration report stronger performance.

Digital Recruitment Tools

Modern recruitment platforms which are powered by AI and data analytics helps HR departments to identify innovation aligned candidates more effectively. Meijerink et al. (2024) note that digital HRM systems can assess candidates not just for technical competency but also for indicators of innovativeness such as lateral thinking, adaptability and openness to learning. This improves person to job and person to organization fit.

The use of digital tools enhances innovative outcomes by accelerating the recruitment cycle for high demand innovation roles which is done by reducing bias in selection and ensuring a better match between job requirements and creative potential.

2.1.2. Training and Development

Training and development are also essential for developing the human capital needed to drive innovation. Bornay-Barrachina et al. (2017) supports that training investments build both human and social capital significantly impact a firm's innovation performance.

Human and Creative Capital

At the heart of training and development lies the enhancement of human capital which refers to the technical skills and knowledge employees bring to the workplace. Veenendaal (2015) emphasizes that HRM practices enhance employees creative capital such as training programs focused on creativity techniques and problem solving skills are essential for fostering an innovation-oriented workforce. Creative capital refers to employees ability to generate novel ideas and solve complex problems both of which are critical factors for innovation in organizations.

When employees view training and development opportunities as beneficial they are more likely to feel equipped to generate new ideas. Shipton et al. (2006) found that relative to other HR practices training had the most significant impact on product innovation and innovations in technical systems. Zhang and Begley (2011) has also demonstrated a strong positive relationship between training and development practices and innovative work behavior (IWB).

Organizations that offer continuous learning opportunities such as leadership development, skill workshops and knowledge sharing sessions create a workforce that is more adaptable to change and ready to contribute to innovative solutions. According to Bornay-Barrachina et al. (2017) when HRM invests in training it sends a clear message to employees that their contributions to innovation are valued which increases their commitment to the organization's long-term innovation goals.

Cognitive Flexibility

Training programs foster cognitive flexibility which is the ability to think creatively and shift between different problem-solving approaches are quite essential for driving innovation. Cognitive flexibility helps employees to approach problems from multiple angles, experiment with new solutions and adapt to changing circumstances. Veenendaal (2015) highlights that employees with high cognitive flexibility are better equipped to solve complex and novel problems which is again essential in an innovation-driven work environment.

HRM's role is not only to improve employees' technical abilities but also to nurture their cognitive and emotional capabilities such as resilience, creativity and the ability to collaborate across disciplines. Bos-Nehles and Veenendaal (2019) note that employees who receive training in creativity and critical thinking are better prepared to participate in innovative work processes. Training encourages employees to step outside their comfort zones, challenge assumptions and experiment with new methods is critical for innovation particularly in environments that require high levels of creativity and problem-solving.

Training and Development in Collaborative Innovation

Innovation increasingly occurs through collaborative efforts which requires employees to work together across teams, departments and even organizational boundaries. T&D programs focus on collaborative skills such as communication, conflict resolution and team coordination are essential for ensuring that employees can contribute effectively to innovation projects.

Hong et al. (2019) argue that training aimed at enhancing teamwork and interpersonal skills is particularly valuable in organizations that rely on cross-functional collaboration for innovation. Training programs emphasize interdisciplinary collaboration help employees bring diverse perspectives and knowledge to the table which is crucial for creating breakthrough innovations.

When working with external partners such as suppliers, customers and even competitors, training programs must also address the skills necessary for external collaboration. Bos-Nehles and Veenendaal (2019) discusses the role of information sharing as a key aspect of collaborative innovation. Organizations that encourage transparency and open communication through training initiatives are more likely to succeed in their innovation efforts as employees share knowledge freely and work together to co-create new solutions. HRM's role in facilitating collaborative training ensures that employees are equipped to engage with external stakeholders and leverage external knowledge effectively for innovation.

Effect of Innovative Climate

Training programs are more effective when they are delivered within an innovative climate which is an environment that actively supports and encourages creativity, experimentation and risk taking. Bos-Nehles and Veenendaal (2019) found that the moderating effect of an innovative climate plays a significant role in enhancing the relationship between T&D and innovative work behaviour. When employees perceive the organizational climate as supportive of innovation then training and development initiatives have a stronger effect on their engagement in innovation-related activities. In an innovative climate employees feel more empowered to apply the skills they have gained through training as they know that their contributions will be valued and rewarded. Additionally Sung and Choi (2018) also note that employees perception of HRM practices such as development-oriented training can significantly affect their engagement in innovation especially when supported by an innovative climate.

Developmental opportunities focus on exploratory skills foster ambidextrous innovation by helping employees to balance exploitative and explorative tasks (Park et al., 2019). Firms that prioritize broad continuous learning rather than short-term task-specific training are better positioned to create innovative work behavior (Andreeva et al., 2017). Bos-Nehles and Veenendaal (2019) highlight that information sharing and supportive supervision are two critical HR practices that are enhanced in an innovative climate. Information sharing encourages employees to exchange knowledge and ideas while supportive supervision ensures that employees feel supported and motivated to pursue innovative tasks more about which will be discussed in section. Training that promotes these practices with an innovative climate leads to stronger levels of IWB as employees are more likely to apply their new skills in ways that contribute to the organization's innovation.

Digital Learning Platforms

Digital learning platforms have become an essential tool for delivering training programs that foster innovation. These platforms allow employees to access training materials, participate in webinars and collaborate with colleagues across the globe. According Meijerink et al. (2024) digital HRM systems help streamline the delivery of training which ensures that employees are continuously learning and staying up to date with the latest technologies and innovation practices.

2.1.3. Performance Management

Performance management (PM) systems can significantly influence innovation outcomes depending on how they frame goals, feedback and evaluations. Traditional performance management systems that emphasize routine tasks or short-term productivity can disrupt innovation by discouraging risk taking and exploration. In contrast to traditional system innovation aligned performance management systems focus on learning outcomes, experimentation and team contributions. As Sung and Choi (2018) note strong alignment between performance management systems and an innovative climate supports and amplifies the positive effects of HR practices on innovation.

Performance Metrics

The key to using performance management effectively for innovation lies in aligning performance metrics with innovation goals. As Veenendaal (2015) notes an innovation-driven performance management system goes beyond traditional individual output metrics and focuses on teamwork, creativity and problem-solving. By including innovation related goals into performance appraisals such as the development of new products, services or processes the organizations ensure that innovation becomes a core component of employee performance evaluations. This system motivates employees to actively participate in the innovation process as their contributions to creativity and problem solving are directly linked to their success and career progression within the company.

The integration of innovation-related KPIs into PM systems encourages employees to take initiative and experiment with new ideas without the fear of failure which is quite essential for supporting an innovation culture. Andreeva et al. (2017) notes that employees who perceive their work environment as supportive and development oriented are more likely to engage in innovative work behavior. Regular feedback and recognition are critical elements of PM systems as they not only guide employees progress but also reinforce the importance of innovation in the organizational culture.

Supportive supervision

Supportive supervision is another crucial component of performance management that significantly impacts innovation. Employees who receive continuous and constructive feedback from their supervisors are more likely to feel valued which enhances their motivation to contribute creatively. Managers who encourage risk taking, acknowledge innovative ideas and provide developmental feedback help to support an environment where innovation can flourish. Veenendaal (2015) highlights that supportive supervision is positively correlated with innovative work behaviour (IWB) particularly when employees perceive their supervisors as genuinely interested in their personal and professional growth. This behaviour oriented supervision encourages employees to experiment, take calculated risks and contribute innovative solutions to organizational challenges.

In addition to supporting innovation a feedback rich PM system also reduces the psychological barriers that employees face when suggesting new ideas. According to Bornay-Barrachina et al. (2017) HR practices that involve supportive supervision create a safe space for employees to voice ideas without the fear of rejection or punishment. This safety is essential for innovation as it encourages employees to share and build on new ideas which ultimately contributes to both incremental and radical innovations within the organization.

Performance Appraisals

Performance appraisals are an integral part of performance management systems and serve as a means of recognizing employees contributions to innovation. However, traditional performance appraisals often fail to adequately capture the behaviours and activities that drive innovation. Hong et al. (2019) emphasize that performance appraisals should be designed to assess not only traditional metrics of productivity but also innovative work behaviours (IWB). IWB includes activities such as idea generation, championing ideas and applying innovations in the workplace. These behaviours are often voluntary and significantly influence organizational innovation but they are not always reflected in traditional performance appraisal systems.

The implementation of innovation specific performance appraisals also allows organizations to formally recognize and reward employees for their contributions to creativity and innovation. For example PM systems incorporate IWB dimensions such as idea development, implementation and knowledge sharing encourages employees to actively contribute to the innovation process. As Veenendaal (2015) suggests organizations expand their performance appraisal systems to include multiple stages of innovation such as the initiation, development and application of new ideas. This ensures that employees contributions to innovation are appropriately valued and incentivized.

In case of external collaborations performance appraisals also recognizes the collaborative behaviours that support innovation. Hong et al. (2019) argue that team-based appraisals are particularly effective in fostering open innovation as they encourage knowledge sharing, cross-functional collaboration and the collective generation of new ideas. These team-based performance metrics provide a sense of shared responsibility for innovation which is essential for organizations that rely on external partnerships and collaborative networks for innovation.

Explorative Vs Exploitative Innovation

Moving on to ambidextrous innovation which involves balancing exploitative innovation (incremental improvements) with exploratory innovation (radical new ideas) is another critical component in performance management systems. Park et al. (2019) explores how high-commitment HRM systems support ambidextrous innovation by integrating performance management practices that simultaneously encourage the refinement of existing technologies (exploitation) and the exploration of new and disruptive ideas (exploratory). By balancing both dimensions organizations ensures that they continue to improve existing products while also remaining open to radically new concepts that could potentially disrupt the market.

Performance management systems incorporate both short-term and long-term innovation goals. Park et al. (2019) argue that PM systems incentivize employees to not only focus on immediate improvements but also dedicate time and resources to experimenting with novel ideas. The ability to integrate both exploration and exploitation into performance appraisals ensures that organizations do not stagnate but continue to innovate.

Additionally, supportive performance management encourages both types of innovation help employees navigate the potential conflicts that arise between exploiting existing capabilities and exploring new possibilities. As Naqshbandi et al. (2023) note HRM systems that support ambidextrous behaviours enhance organizational resilience and adaptability which is essential in environments where technological change and market dynamics are constantly evolving.

Digitalization

The digitalization of performance management systems is becoming increasingly important in supporting innovation in organizations. Meijerink et al. (2024) highlights the growing role of digital platforms in aligning performance metrics with organizational innovation goals. Digital tools such as real-time feedback systems and performance dashboards provide organizations with the ability to monitor innovation progress continuously and make adjustments to HR practices in real-time. These tools help managers assess employees contributions to innovation more dynamically which ensures that feedback is timely and relevant.

Digital PM systems also allow for a more personalized approach to innovation management. By using data analytics to track employees innovation contributions the organizations offer tailored development plans that focus on enhancing specific skills or addressing knowledge gaps. This personalized feedback loop is essential for supporting innovation as it helps employees stay aligned with organizational goals while continuously developing the competencies required to drive innovation (Lindblom and Martins, 2022.

2.1.4. Rewards and Compensation

Reward systems play a critical role in motivating employees to innovate. Incentive structures which recognize idea generation, cross-functional collaboration and long-term value creation support a culture of innovation (Charlwood and Guenole, 2022; Andreeva et al., 2017).

The foundation of a successful rewards and compensation system for innovation is alignment with the organizations innovation strategy. Reward systems that are perceived as fair and transparent where employees are rewarded for their contributions to innovation which can stimulate creativity and innovative behaviours.

Andreeva et al. (2017) highlights the importance of aligning reward structures with the strategic goals of the organization noting that HR practices that recognize and incentivize knowledge sharing, collaboration and risk taking are essential in promoting innovation. This alignment ensures that employees understand that innovation is a priority and that their efforts in this area will be rewarded.

Veenendaal (2015) focuses on the fact that when compensation is linked to innovation related outcomes such as the development and implementation of new ideas, products or services it motivates employees to focus on longer-term and value-creating activities. Without such alignment employees may become focused solely on short-term and performance-driven goals which fail to contribute to the organization's innovation objectives.

Similar to performance management when discussing about external collaborations rewards system that recognizes collaborative efforts are quite important. Hong et al. (2019) discuss that reward systems that incentivize team based innovation rather than just individual achievements are critical in a collaborative culture necessary for open innovation. These systems encourage employees to look beyond their individual goals and engage with external partners and sharing knowledge and co-developing innovative solutions.

Intrinsic vs. Extrinsic Motivation

A critical consideration in reward systems for innovation is the balance between intrinsic and extrinsic motivation. While extrinsic rewards such as bonuses, salary increases and promotions provide immediate motivation for innovative behavior while intrinsic motivation which comes from a genuine interest in the work is also quite essential for long-term creativity and problem-solving. Amabile (1996) suggests that intrinsic motivation plays a vital role in creativity as individuals are more likely to generate novel ideas when they are motivated by the work itself rather than by external rewards. This is especially true in complex and open ended innovation tasks where creativity and experimentation are key.

Bornay-Barrachina et al. (2017) highlights that a well-rounded reward system includes both intrinsic and extrinsic components to create an environment where innovation thrives. Extrinsic rewards such as financial compensation are important for recognizing and reinforcing the value of innovative contributions while intrinsic rewards such as recognition, opportunities for personal growth and a supportive work environment helps sustain long-term creativity and innovation efforts.

Research suggests that when employees perceive extrinsic rewards as controlling it can undermine their intrinsic motivation (Deci et al., 1999). Therefore, the key is to ensure that rewards for innovation are seen as a recognition of effort and achievement rather than as an attempt to control behaviour.

Performance-Based Rewards

Performance-based rewards are widely used in HRM systems to link individual contributions to organizational outcomes. In the context of innovation performance-based rewards are particularly effective in motivating employees to engage in innovative behaviours.

Veenendaal (2015) emphasizes that performance-based rewards for innovation are not only tied to financial or output-related metrics but should also account for the development of new ideas, the application of knowledge and the collaboration necessary to bring ideas to fruition. For example, companies reward employees for participating in cross-functional teams, leading innovation projects or contributing to new product development processes. These types of rewards encourage employees to think creatively and take risks, knowing that their contributions to innovation will be valued.

Similarly, Park et al. (2019) discuss that for HRM systems to support ambidextrous innovation where both exploration (radical innovation) and exploitation (incremental innovation) are encouraged performance-based rewards recognize both types of innovation. HRM practices that reward employees for both types of innovation ensures a balanced approach that drives long-term competitiveness.

Team-Based Rewards

Coming to in team collaborative innovation where employees work together to develop new ideas and solutions team-based rewards are particularly effective. Collaborative-based HRM practices as discussed by Hong et al. (2019) focuses on the importance of rewarding teamwork and collective innovation efforts rather than individual achievements. Team success rewards in innovation encourages a culture of knowledge sharing, collaboration and mutual support which are key elements of open innovation.

Meijerink et al. (2024) further argue that in innovation driven environments HRM systems integrate collaborative incentives such as group bonuses or profit-sharing schemes which align the goals of individual employees with the broader objectives of the team or organization. By providing rewards for team-based achievements HRM supports a sense of collective responsibility for innovation and encourage employees to engage in cross-functional and interdepartmental collaborations.

Naqshbandi et al. (2023) observe that reward systems prioritize knowledge sharing and collaboration over individual performance help to reduce the barriers to open innovation. These reward structures create an environment where employees feel incentivized to contribute their ideas and expertise to collective innovation projects knowing that their contributions will be recognized and rewarded.

Non-Monetary Rewards

While financial incentives are often the most visible form of rewards and compensation non-monetary rewards also play an essential role in fostering innovation. Non-monetary rewards such as recognition, career development opportunities and access to challenging projects significantly enhance employees sense of autonomy and competence which are two key drivers of intrinsic motivation (Ryan and Deci, 2000).

Sung and Choi (2018) highlights the importance of an innovation-oriented work environment where employees feel empowered to share their ideas and contribute to innovation efforts. Non-monetary rewards such as public recognition, opportunities for skill development and participation in strategic decision-making further reinforces an innovation culture. By recognizing and valuing employees innovative efforts through these non-financial means HRM systems fosters a deeper commitment to innovation and increase long-term engagement in creative problem-solving.

Additionally, Veenendaal (2015) underscores that a supportive organizational culture that celebrates innovation and provides intrinsic rewards such as autonomy and professional growth is essential for sustaining employee driven innovation. This type of culture encourages employees to take risks, experiment with new ideas and collaborate across boundaries while knowing that their contributions to innovation are valued not just in terms of financial rewards but also in terms of personal and professional growth.

2.1.5. Employee Driven Innovation

Employee-Driven Innovation (EDI) refers to innovations that originate from employees who are not formally assigned innovation roles which are typically outside of R&D or strategy departments. These bottom-up initiatives are often driven by employees practical knowledge, contextual insights and intrinsic motivation. HRM as a system that governs people-related processes in organizations plays a central role in enabling, sustaining and scaling such innovation (Kesting and Ulhøi, 2010).

HRM serves as both a facilitator and amplifier of EDI by shaping the conditions under which employees feel empowered to innovate. Renkema et al. (2022) identify two critical dimensions of EDI which are content (idea generation) and process (idea implementation) which are influenced by HRM. Practices such as targeted recruitment, training, job design and supportive supervision directly enhance employees' collaborative and cognitive capacities which are essential for innovation.

These practices are especially vital in formalized environments where strict procedures may hinder spontaneous innovation. For example Renkema et al. (2022) found that even in regulated industries like medical laboratories HR strategies such as cross-functional teaming, informal recognition and open communication helped legitimize and channel employee innovation efforts. HRM also lays the groundwork for operationalizing EDI through systems that capture, develop and institutionalize employee ideas. Tools like suggestion systems and internal innovation platforms are crucial but their success depends on strategic alignment and managerial support. Miao and Ji (2020) in their study of state owned enterprises (SOEs) in China found that suggestion schemes failed where top managers lacked firm-specific knowledge and a long-term commitment to innovation. These findings underscore the importance of leadership stability and contextual understanding in making EDI mechanisms effective.

HRM contributes by designing feedback and reward systems that signal value for innovation. Formal incentives such as performance bonuses and informal methods such as verbal recognition and visibility in organizational communications help sustain employee engagement (Miao and Ji, 2020).

Beyond systems, HRM plays a critical role in shaping the organizational culture and leadership behaviour necessary for EDI to thrive. As Kesting and Ulhøi (2010) argue that expanding employee participation in innovation reflects a broader democratization of work life, aligning with values of autonomy, inclusion and development. HRM fosters this through participatory practices, empowerment strategies and training that promotes psychological safety and risk tolerance.

By investing in leadership development HRM ensures that managers understand their role as facilitators of innovation. A culture that supports experimentation and tolerates failure which are two key pillars of innovation that depends on leaders who coach rather than control. These leadership behaviours are most effective when they are embedded in and reinforced by HR systems (Kesting and Ulhøi, 2010).

The effectiveness of HRM in promoting EDI depends on alignment at both structural and cultural levels. Structurally, HR must embed innovation into the workflow through formal channels such as innovation labs, suggestion platforms and agile teams. Culturally, HR nurtures an environment of psychological safety, learning and trust. Employees are unlikely to share unconventional ideas if fear of failure or ridicule looms large.

Kesting and Ulhøi (2010) highlights that EDI thrives in cultures that reflect democratic values where participation and equality are emphasized. This includes flattening hierarchical barriers, promoting inclusive dialogue and treating innovation as a collective and ongoing process rather than a top-down initiative. The effectiveness of HRM in supporting EDI depends heavily on how employees perceive HR policies in practice. When HRM is seen as empowering and coherent with organizational innovation goals, employees are more likely to reciprocate through proactive behaviours such as knowledge sharing and intrapreneurship (Miao and Ji, 2020).

HRM must also remain adaptive particularly during periods of digital transformation or organizational restructuring. Agile HR strategies such as iterative performance reviews, innovation oriented KPIs and dynamic team formation are quite essential for maintaining EDI.

2.2. AI integration in HRM

In this section we will look at what all AI tools and algorithms are used in HRM currently and what could be integrated in HRM. Additionally, we will also look how these AI features augment HRM practices which will lay the foundation for analyzing the innovation outcomes which will be further down in the report. We will also look at few critics of the use of AI in HRM. Also for this section we will be focusing on the four core functions categories that we have prepared.

2.2.1. AI in Recruitment and Selection

Recruitment is one of the most transformed HR functions and uses the most artificial intelligence features. AI is deployed in various recruitment stages such as job advertisement targeting, candidate sourcing, resume screening, psychometric assessment, interviewing and onboarding which makes the process faster, more consistent and scalable (Budhwar et al., 2022; Gong et al., 2025). The level of AI integration in recruitment varies based on organizational size, digital maturity and local labour laws. Additional complexities such as cross-border compliance, linguistic diversity and cultural fit assessments arise when we take HRM function on an international level (Budhwar et al., 2022).

Currently the AI tools used in recruitment include applicant tracking systems (ATS), AI-based interview platforms, gamified assessments and chatbots. HireVue which is a leading platform uses AI to analyze facial expressions and vocal characteristics in video interviews to assess candidate potential (Diefenhardt, 2025). Pymetrics analysis which is also a part of recruitment assessments uses neuroscience-based games and machine learning algorithms to evaluate candidates cognitive and emotional attributes. AI chatbots like Mya which is developed by Mya systems handle applicant FAQs and schedule interviews Charlwood and Guenole (2022) further assisting recruitment and applicants. AI-powered sourcing tools like Entelo and X0PA AI Recruiter scrape data from professional sites to identify passive candidates who match job profiles (Koch-Bayram and Kaibel, 2024).

Algorithms used include supervised learning models such as logistic regression and random forest are used to predict candidate suitability. Natural language processing (NLP) algorithms extract keywords and context from resumes and job descriptions to match candidate profiles. Clustering algorithms help group applicants based on skill similarity and reinforcement learning algorithms continuously improve recommender systems based on recruiter feedback (Gong et al., 2025; Heidemann et al., 2024).

AI supports faster and scalable screening while improving the quality of hire through data-driven recommendations. It helps mitigate human bias as the provided models are trained on unbiased data which ensures consistent evaluations (Pan et al., 2022; Budhwar et al., 2022). AI is also useful for enhancing candidate experiences through real-time communication and status updates (Koch-Bayram and Kaibel, 2024).

Even though the AI models are promised to be trained on unbiased data algorithmic bias remains a concern. As Diefenhardt (2025) points out opaque algorithms can replicate historical discrimination unless carefully monitored. Legal frameworks such as GDPR require organizations to ensure transparency in automated hiring decisions (Charlwood and Guenole, 2022).

2.2.2. AI in Training and Development

AI technologies that are implemented in training and development enhance personalization, skill tracking and learning outcome measurement. With the rise of hybrid work and digital transformation organizations are now increasingly relying on AI to offer scalable and adaptive learning solutions (Malik et al., 2023; Gong et al., 2025). However critics argue that over-personalization and lack of human feedback can hamper collaborative learning. Transparency about how AI recommends or alters content is crucial for user trust. If the Ai has not been trained properly using data which is diverse then the underrepresented groups may face challenges (Charlwood and Guenole, 2022).

Currently the AI tools used in training and development function include Adaptive Learning Management Systems (LMS), intelligent tutoring systems, Artificial reality or virtual reality platforms and microlearning applications. Tools such as Saba Cloud, Cornerstone OnDemand and EdCast integrate AI for real-time feedback and content recommendation. AI-powered virtual coaches and bots guide learners based on their past performance, preferences and goals (Budhwar et al., 2022).

Advanced platforms use behavioural data to predict which learners are likely to struggle and provide proactive solutions and recommendations. A widely used example of this would be Docebo which uses NLP and machine learning to curate and adapt content to employee needs. AI-enhanced VR/AR systems simulate real-world tasks for hands-on training (Mirowska and Mesnet, 2022; Charlwood and Guenole, 2022).

Algorithms currently used are reinforcement learning enables content adaptation based on learner feedback and clustering algorithms categorize employees by learning pace and style. Deep learning is used to predict learning outcomes based on behavioral and performance indicators. Predictive models are also used and can offer personalized learning paths (Gong et al., 2025).

The benefits of the integration include continuous, accessible and contextual training which increases learner engagement and retention (Malik et al., 2023). It also supports rapid reskilling which is quite critical in fast-evolving industries. The system also provides real-time insights into training effectiveness which helps in better alignment of learning with strategic goals of the organisation. (Koch-Bayram and Kaibel, 2024).

2.2.3. AI in Performance Management

With implementation of AI performance management has evolved from annual reviews to real time and data driven processes. AI in this case monitors workflows, evaluates KPIs and provides timely feedback to both managers and employees (Malik et al., 2023; Gong et al., 2025). While the benefits are clear the critics also highlight that excessive surveillance can damage trust and psychological safety of the employees. The implications of continuous monitoring should be addressed with transparent policies and opt-in practices (Diefenhardt, 2025; Mirowska and Mesnet, 2022). This can be done by using explainable AI (XAI). Explainable AI is a variant of AI systems designed to make their decisions understandable to humans. XAI provides a clear and traceable reasoning behind AI outputs (Samek et al., 2019).

AI tools and systems implemented in performance management include softwares such as Workday, Betterworks and Lattice which track performance and flag declining engagement so that HR managers can suggest coaching programs. Chatbots are also used in performance management to provide real-time coaching based on ongoing project metrics. NLP tools are used to analyse communication tone and volume across digital platforms such as Slack and Outlook to evaluate and gauge employee morale (Budhwar et al., 2022). AI-powered dashboards visualize trends in productivity and engagement. Additionally in some physical labour intensive industries such as manufacturing and healthcare wearables and sensors are used to track physical fatigue and alert managers of burnout risk (Koch-Bayram and Kaibel, 2024)

Currently algorithms used include Sentiment analysis using NLP to interpret emotional tone from text communications, predictive models to forecast high-potential employees based on historical performance. Fuzzy logic and multi-attribute utility models are used to integrate multiple qualitative and quantitative dimensions to assess performance (Budhwar et al., 2022).

The benefits include reduced subjectivity and providing continuous performance feedback, improving productivity and satisfaction (Wiblen and Marler, 2021). AI systems also flag issues such as performance dips using which manager can help personalize developmental goals for employees (Clavel et al., 2025).

2.2.4. AI in Compensation and Rewards

AI tools are increasingly used in compensation and rewards to drive pay equity, personalize benefits and optimize compensation structures. These systems support HR managers in analysing compensation fairness and linking rewards to performance (Budhwar et al., 2022; Gong et al., 2025). Here also AI has similar dangers as mentioned above such as lack of clarity on algorithmic decision-making can trigger resistance. Fairness-aware ML models along with regular audits and human oversight are quite essential here to avoid reinforcing systemic biases (Charlwood and Guenole, 2022; Heidemann et al., 2024)

AI tools used in this function include platforms such as beqom, Salary.com and Compport which analyse internal pay data and market benchmarks to suggest salary adjustments. They can also help tailor benefits packages using employee preference data (Koch-Bayram and Kaibel, 2024). Predictive compensation modeling is also used to forecast salary trends and budget implications (Meijerink et al., 2024). Chatbots are used here to answer employee queries about compensation policies, enhancing transparency and access to information.

Algorithms used here include regression analysis estimates appropriate pay based on role, tenure and geography which clusters employees with similar profiles for targeted incentive programs (Meijerink et al., 2024). Optimization algorithms are also used which allocate reward budgets across departments while meeting equity goals (Saidi Mehrabad and Fathian Brojeny, 2007)

Finally the benefits include enhance transparency, reduce pay gaps and support compliance with equal pay laws while using AI driven payments system. While personalization improves employee satisfaction by aligning compensation with individual needs (Budhwar et al., 2022).

2.3. Challenges

Here in this section we will explore what are the challenges employees and organisations face when aligning HRM and innovation. After which we will explore what are the challenges faced by HRM when integrating Artificial Intelligence and challenges regarding HRM, AI and innovation in general.

2.3.1. HRM and Innovation

While Human Resource Management (HRM) is widely acknowledged as a key component for innovation but organizations frequently encounter significant challenges when attempting to align HRM practices with innovation outcomes. These challenges mostly result due to tensions between short-term efficiency and long-term creativity, misaligned HR systems, inconsistent implementation, limited employee engagement and contextual constraints such as rigid organizational structures or lack of managerial support. The research across multiple studies highlights that HRM if not strategically aligned or effectively executed can hinder innovation. This section will explore deep into such challenges:

Misalignment Between HR Practices and Innovation Goals

One of the foremost challenges is the misalignment between HRM systems and innovation strategies. As Andreeva et al. (2017) notes that when HR practices such as performance appraisal, compensation and training are not cohesively designed to support and encourage innovation then they may send mixed signals to employees which creates confusion or even resistance. For example performance management systems that emphasize efficiency and error-free execution can discourage experimentation and risk-taking behaviours which are critical to innovation. In their analysis of interaction effects Andreeva et al. (2017) notes that HRM practices can backfire when they are implemented in conflicting ways which results in reduced innovative performance. Chowhan (2016) notes that many firms continue to evaluate employee performance based on standardized productivity metrics that reward predictability and incremental output. Such systems are not suited for environments where breakthrough innovation, experimentation and iterative development are required. Due to such systems highly creative employees may censor or disengage from proposing innovative ideas if they believe these behaviors will not be rewarded or worse they may attract negative evaluations.

Veenendaal (2015) also notes that while many organizations state innovation as a strategic goal they still continue to prioritize operational fit which is hiring candidates based on technical proficiency and role alignment over creativity, adaptability or collaborative capacity. This results in talent pools which are optimized for short-term execution rather than long term exploration.

Bos-Nehles and Veenendaal (2019) found that trainings impact on innovative work behaviour (IWB) depends on whether employees perceive the organization as supportive of innovation or not. Without an innovation supportive climate or performance feedback mechanisms employees often see training as an obligation or as a means to improve efficiency rather than as a tool for creative growth. This gap limits the practical application of new skills in innovation efforts. Even though the organisation provides high quality training employees fail to link learning outcomes with real world innovation projects.

Veenendaal (2015) highlights a famous misalignment which can termed as the "innovation rhetoric practice gap". It is a situation where organizations promote innovation in public statements and strategy documents but fail to back this with its HR systems which fails to support or reward it. When HR policies and leadership behaviours are not aligned with the innovation message employees will perceive innovation as superficial or insincere which results in disengagement or lack of trust.

Overstandardization

Innovation thrives in flexible and adaptive environments. But overly standardized HR practices can hinder creative behaviours. Chowhan (2016) notes that many organizations particularly those in manufacturing sector heavily rely on rigid control oriented HR systems that hinders the autonomy. Even high performance work systems (HPWS) can lose effectiveness when deployed in overly bureaucratic settings where employee creativity is not structurally supported or encouraged.

This lack of flexibility is particularly problematic in large or traditional organizations that prioritize uniformity over experimentation. According to Bos-Nehles and Veenendaal (2019) employees may perceive training and development initiatives as tools for compliance or efficiency rather than for personal growth or innovation especially when innovation is not clearly rewarded or structurally supported.

Veenendaal (2015) discusses that when training programs designed to enhance operational efficiency or technical competency without an emphasis on creativity and critical thinking can lead employees to become more focused on maintaining the status quo rather than challenging it. Similarly Bos-Nehles and Veenendaal (2019) found that employees who participate in training programs that focus on technical proficiency rather than innovation or creativity are less likely to demonstrate innovative work behavior (IWB).

Andreeva et al. (2017) also notes that when HRM practices emphasize strict monitoring, error-free performance and short-term results they may create a risk-averse culture that is detrimental to innovation. Employees may avoid suggesting new ideas or solutions that deviate from the norm fearing negative evaluations or reduced rewards. Additionally, Bos-Nehles and Veenendaal (2019) notes that performance management systems that overlook or under reward the early stages of innovation such as idea generation or experimentation often fail to encourage employees to engage in these crucial activities.

Ineffective Communication

Another frequently cited barrier is the gap between intended and perceived HR practices. Employees view HR practices through the lens of their personal experiences which may not align with the strategic intent of HRM. Wright and Nishii (2013) supports this distinction between ”intended”, ”implemented” and ”perceived” HR practices and if these are not maintained then it can can lead to poor employee engagement with innovation initiatives (Ko & Ma, 2019).

Bos-Nehles and Veenendaal (2019) confirm this in their empirical study where they found that certain HR practices such as training and compensation only influenced innovative work behavior (IWB) when employees perceived them as supportive and relevant to innovation. When this perception was absent even well-designed HR initiatives failed to generate innovative outcomes.

Recruiting for Innovation

Veenendaal (2015) notes that while technical expertise is essential organizations must also recruit individuals who exhibit creative capital. But creativity oriented traits such as cognitive flexibility, risk-taking and a willingness to experiment are not easily identifiable through conventional resumes or interviews.

Recruitment processes that focus primarily on technical skills or experience can overlook creative individuals who may not have the conventional qualifications but possess significant potential to drive innovation. Bornay-Barrachina et al. (2017) supports this claim that narrow focus may result in a homogeneous workforce that lacks the diverse thought processes necessary to generate new ideas.

Another challenge in recruiting for innovation is managing the diversity of innovative profiles. Different types of innovation require different kinds of talent such as incremental innovations may require employees with deep industry knowledge while disruptive innovations might require individuals with an entrepreneurial mindset or a high tolerance for ambiguity and risk. Hong et al. (2019) points out that failing to differentiate between these types of innovation can lead to mismatched hires which results in poor innovation performance.

2.3.2. Challenges for AI and HRM

The integration of Artificial Intelligence into Human Resource Management offers many opportunities for improving efficiency, decision-making and personalization. But this transformation also brings significant challenges that organizations must address to successfully adopt AI technologies in their HR practices.

Bias in AI

One of the major challenges of AI in HRM is the potential for algorithmic bias. AI systems often learn from historical data and if that data reflects biased or discriminatory practices then AI models can replicate these biases. This issue is particularly concerning in recruitment, performance evaluations and compensation where AI tools could reinforce gender, racial or socioeconomic differences (Heidemann et al., 2024; Charlwood and Guenole, 2022). This type of bias is particularly difficult to detect in highly complex AI models such as deep learning networks which further complicates the issue (Budhwar et al., 2022).

Employee Trust and Resistance

Employee resistance to AI is another significant challenge in HRM. Many employees fear that AI will replace humans or lead to unfair treatment in performance evaluations and compensation. This resistance is often because of concerns about surveillance, loss of autonomy and the potential lack of human empathy in AI systems (Malik et al., 2023). HR professionals need to ensure that AI is implemented in a way that complements rather than replacing human judgment. Addressing these concerns requires clear communication about how AI is being used.

Data Privacy and Security

AI in HRM operates on datasets that include personally identifiable information (PII) such as names, locations, education history, health data and job performance metrics.

In more advanced systems data on facial expressions, speech patterns or mouse movement is captured for analysis (Koch-Bayram and Kaibel, 2024; Malik et al., 2023). The sensitivity of this data increases the risk of harm if it is misused, leaked or exposed to unauthorized parties.

One particularly development in AI-driven HRM is the potential for shadow profiling where AI builds comprehensive behavioural or psychological profiles of employees using inferred data rather than explicitly provided information. AI might assess stress levels based on typing speed or evaluate productivity based on calendar activity (Diefenhardt, 2025). While this may helps organizations but it could also introduce the risk of data misuse such as using inferred mental health data to screen out candidates or justify dismissals.

Quality and Availability of Data

AI systems require large volumes of high quality data to function effectively. But many organizations face challenges in collecting, cleaning and maintaining accurate and comprehensive datasets. In HRM system the data used to train AI systems often comes from a variety of sources such as employee surveys, performance reviews, attendance logs and social media profiles which can be inconsistent or incomplete.

The quality of historical HR data can impact the performance of AI models. If historical data is biased, incomplete or not representative of the full employee base then the AI model will likely produce inaccurate or skewed results. Budhwar et al. (2022) notes that without high-quality and representative data AI systems in HRM could fail to make valid decisions or unintentionally reinforce existing biases which further complicates the HR process (Gong et al., 2025).

Implementation Costs

The cost of implementing AI in HRM can be a barrier for many organizations particularly for small and medium sized enterprises (SMEs). Developing, testing and deploying AI systems often requires significant investment in technology, training and infrastructure. The integration of AI into existing HR systems could require a major organizational shift such as changes in workflows, employee roles and company culture. Organizations must carefully assess their readiness for AI adoption including their ability to manage the technical, financial and cultural aspects of AI integration. Successful AI implementation requires a strong foundation in both technology and human resources while providing continuous support for employees as they transition to new roles (Tambe et al., 2019; Pereira et al., 2023).

3 Methodology

This section outlines the research design and methods employed to investigate the research questions. Given the complexity and novelty of the topic a systematic literature review approach was adopted which will be aided by insights from a few selected interviews from HR managers. First a systematic literature review (SLR) was conducted to comprehensively analyze existing academic research and identify prevailing themes and knowledge gaps related to the subject as seen in chapter 2. Following this semi-structured interviews were carried out to enrich the insights from the literature with practical perspectives from experienced professionals. In addition to these we will add on how the report will be structured and why it is structured in this particular way.

3.1. Research and Report Design

This research is designed as mentioned above as a systematic literature review following PRSIMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines (Page et al., 2021) as seen in figure 3.1. As the context of research in our case is quite novel all the result from literature review would be mostly theoretical so we decided to add a few real world insights from HR professionals, this can be found in chapter 4. In the previous chapter 2 we laid the foundation by providing the theoretical background required for our research which is information about HRM and AI and exploring HRM and innovation and AI integration in HRM.

For our systematic literature we focused on peer reviewed papers from select few English language journals in human resource management sphere that were high credible. This step was taken to ensure that knowledge base we create will be as reliable as possible. The journals we selected were:

- Journal of management
- Human resource management journal
- Human resource management
- International journal of human resource management
- Journal of business research

- Human relations
- Personnel review
- Journal of organizational psychology
- Human resource development quarterly
- Human resource management review

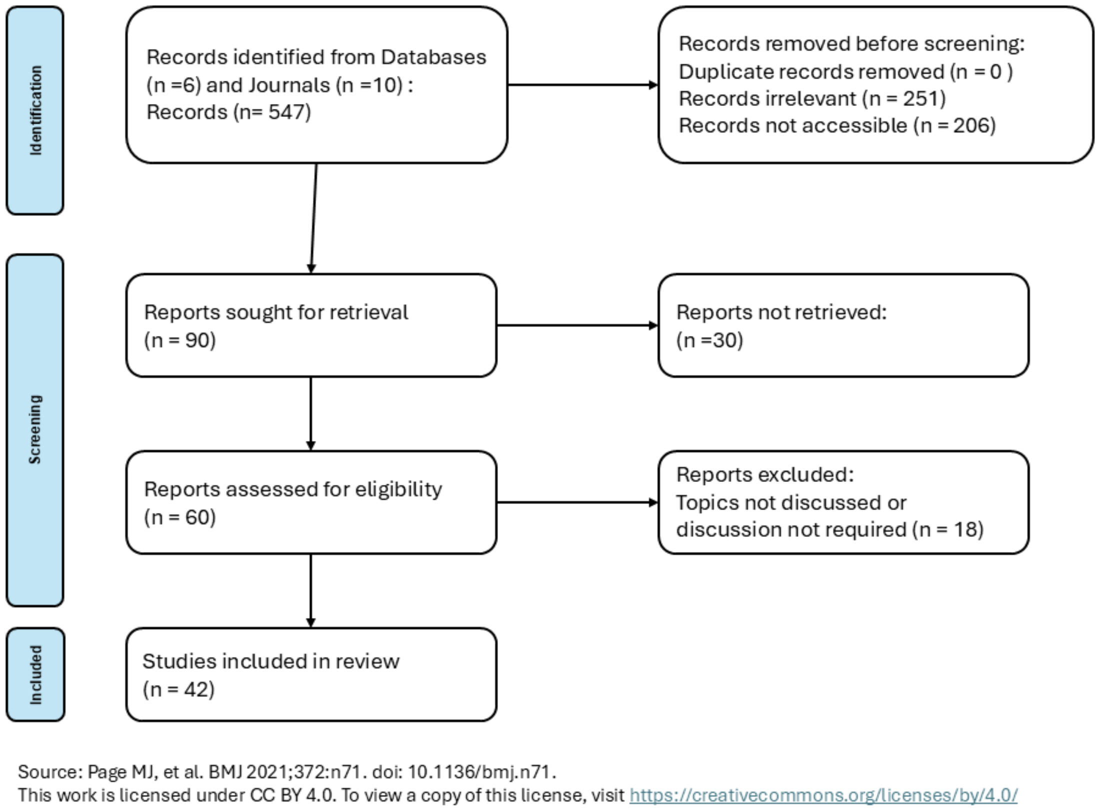

Figure 3.1: PRISMA flowchart

After this we began our search for papers published in these journals. We used keywords such "Artificial Intelligence ", "AI", "AI HRM", "AI integrated", "artificial intelligence and human resource", to find articles that were related to AI integration in HRM. A great benefit for our search that all the articles in these journals were already Human Resource based. To find articles for HRM and innovation we used keywords such as "innovation", "HRM and innovation", "Human resource and innovation", "human resource management and innovation", "innovative", "innovative outcomes" and "employee outcomes". We also decided to place no time restrictions because this is one of the first systematic review done on the relationship between AI integrated HRM and innovation to capture all the available information we can get. After this we narrowed down our scope to ones that would be accessible to us and were in English. We also did a basic elimination by analysing heading and topic and selecting only the ones that will contribute to our research. This reduced significantly reduced the pool of the papers. We now had around 90 articles. Then to find papers that were relevant to our research we went through abstracts. Additionally, we also used a backward and forward snowballing procedure by searching the reference lists of the selected studies for additional works of relevance. This was a time taking process but helped us in our commitment to create a reliable and relevant knowledge base. This process ended with a total of 42 relevant articles.

These 42 articles were studied in detailed and a theme table as seen in the Appendix A table A.1 was created. This theme table highlighted all the key takeaways required to establish the connections between our two main subjects AI integrated HRM and Innovative outcomes.

As discussed before the theoretical background chapter laid the groundwork for the results of the systematics literature review analysis and interviews which are discussed in Results and discussion chapter 4. We also discuss the practical implications of our findings which will be discussed for HR professionals and practitioners in organisations in chapter 5. Additionally, we also discuss the limitations of our research and present some discussions on future research on this topic in chapter 6.Finally, we conclude the report in conclusion chapter 7.

To derive the individual and organizational innovation outcomes presented in the results section, this study relied on a structured review of 42 peer reviewed academic articles exploring the relationship between HRM practices and innovation and AI and HRM. Rather than applying formal thematic analysis the approach involved manually identifying and extracting specific outcomes such as “creative cognitive capacity” which was mentioned in Veenendaal (2015) and “agility through adaptive skill development” which was mentioned in Seeck and Diehl (2017) and Sung and Choi (2018) as practices that lead to innovation outcomes due to HRM practices.

These outcomes were then examined on how AI might influence, support or enhance innovation outcomes. The results presented in section 4 are therefore grounded in careful review and understanding of existing studies. While interviews with HR professionals were conducted their purpose was solely to provide illustrative and contextual insights that complement the literature based findings thus they were not used to generate or substantiate the innovation outcomes themselves.

3.2. Interview Design

The purpose for interviews in this research was not to perform a qualitative analysis but to aid the systematic literature review. The interviews will provide practical insights to the research based on experiences of HR managers hence semi structured interviews were designed. This section will discuss how the interview was designed, the ethics protocol and the target population.

Albers Mohrman and Von Glinow (1990) noted that High tech organizations recruit and employ Highly skilled workforce and invest a lot of capital in research and development which is again a testament to the innovative capabilities of High-tech firms. High tech firms operate in a space where implementation of new technologies is extremely fast making the older technology obsolete thus a constant need for innovation and adaptation.

The structure of these High tech firms help them grow rapidly due to the implementation of these advanced technologies. This makes them perfect for investigating AI integration in HRM which is a fairly new technological advancement and high tech firms are most likely to have this technology implemented. For our target pool will be only considering HR Managers as they would be responsible for AI integration and are the primary users of HRM.

In order to explore the innovative outcomes industry wide we will targeting High firms across across different sectors which in our case is technology, consulting and financial and manufacturing. As these 3 sectors would cover up most of the major sectors and will keep the whole interviewing process simple. Detailed interview protocol, ethics approval procedure and the questionnaire are available in Appendix B.

3.2.1. Sampling Strategy

Sampling strategy is designed to select participants with relevant experience in AI-integrated HRM practices. The target population consists of HR professionals working in high-tech organizations as these firms are typically early adopters of digital technologies and offer a suitable context for examining the intersection of AI-integrated HRM and innovation.

This sampling approach is designed to gain detailed insights into how AI is used in HRM and how it affects innovation based on the experiences of those directly involved not to produce statistically representative results.

To ensure diversity participants were approached from three distinct sectors within the high-tech domain which are semiconductor, consulting and finance and consumer goods manufacturing (FMCG). These sectors provided variation in organizational size, level of AI integration and scope of HRM systems.

Participants were approached through professional networking platforms primarily LinkedIn and invited via personalized messages explaining the research purpose. Due to the niche and emerging nature of the topic only three interviews were conducted. While the sample size is small, each participant offered in depth insights aligned with the goals of research.

3.2.2. Data analysis and Participant list

The participants list is as follows:

Participant ID	Participant	Industry
HRM1	Head of HR planning & Delivery	Semiconductor
HRM2	HR Transformation Manager	Consultancy and Finance
HRM3	HR Manager	Manufacturing, FMCG

Table 3.1: Participant List

Given the limited number of interviews conducted (n = 3) a full thematic coding process was not employed. Instead a qualitative interpretative approach was taken to analyse the interview transcripts. Each transcript was carefully read and reviewed multiple times to gain an in-depth understanding of the participants perspectives and experiences relevant to the research objectives.

Rather than generating broad themes through coding we focused identifying key insights, recurring points of interest and unique viewpoints within each individual narrative. This approach allowed for a context based examination of the data which helped us in preserving the depth and detail of each participant's account.

This process enables a more detailed and nuanced exploration of each participant's responses. Insights derived from this process are discussed in relation to the broader research questions and existing literature. Additionally the interview summaries can be found in Appendix F.

4 Results and discussion

In this section we will discuss the findings from the literature review and establish connections on how AI integrated Human Resource Management impacts Innovative outcomes at an individual level and organisational level. We have already laid the groundwork by first looking at what is HRM and AI. After which we explored role of HRM in supporting innovation and how AI is integrated specific functions of HRM. After conducting a literature review a theme table for all the 42 papers is prepared which highlights what are specific innovation outcomes that can be drawn from each of the paper. The results obtained from the interviews and literature review is summarized in table 4.2 which can be found at the end of this section. The Interview summaries can be found in appendix F for reference.

4.1. Innovation Outcomes at the Individual Level

Artificial intelligence applications in human resource management (AI HRM) change what employees can do (capabilities), want to do (motivation) and are allowed to do (opportunity) (Appelbaum et al., 2000). These three pillars are foundational to innovative work behaviour (IWB) (Bos-Nehles and Veenendaal, 2019). Innovation work behaviour is what leads to innovative outcomes from an individual side.

The table 4.1 presents clear patterns in how AI-integrated HRM practices helps employee innovation by enhancing the Ability, Motivation and Opportunity (AMO) dimensions of work. The literature analysis showed that these AI-driven systems consistently support micro level psychological and behavioural processes that are crucial for innovative outcomes. Interview results are also provide real life evidence that AI driven HRM systems do infact support the micro level psychological and behavioural processes that are crucial for innovative outcomes.

Component	AI-HRM practice	Innovation-relevant process	Evidence	Interview evidence
Ability	AI-driven recruitment & selection	Broader, bias-reduced talent pools increase cognitive diversity an component of creative idea generation	CV parsing and video analysis tools attract and screen candidates on skills which creates quality enhancement features that predict applicant creativity (Koch-Bayram and Kaibel, 2024)	HRM1, HRM3 and HRM2 conformed this by mentioning the use of AI for resume parsing; shortlist quality is higher and more diverse
	Adaptive learning & development platforms	Personalised content and real-time feedback accelerate skill acquisition, boosting “creative self-efficacy”	AI chatbots and VR coaches free up managers training workload while lifting employees perceived mastery (Malik et al., 2023).	HRM1, HRM2 and HRM3 highlighted AI technologies supported workshops and AI literacy training; free employees to focus on new projects
Motivation	Algorithmic performance management	Continuous and predictive feedback signals growth potential and nurtures intrinsic motivation to experiment	Transparent post-hoc explanations of ML turnover models increase trust and willingness to voice ideas (Heidemann et al., 2024).	HRM1 and HRM2 mentioned AI is framed as augmenting not policing; adoption is voluntary creating “positive energy” and proactive experimentation.

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Component	AI-HRM practice	Innovation-relevant process	Evidence	Interview evidence
	Hyper-personalised employee experience bots	Individually curated HR journeys create feelings of support and affective commitment which are strong predictors of voluntary innovative behaviour	Employees served by AI digital assistants report higher commitment and lower exit intentions both of which are linked to proactive innovation (Malik et al., 2023).	From interview with HRM2 we found chatbots to boost perceived support and engagement and similar expectations were placed by HRM1 and HRM3
Opportunity	Cross-functional knowledge-transfer analytics	AI shows hidden expertise networks enabling novel knowledge recombination	HR analytics that map R&D-sales connections reduce peer-to-peer friction and raise opportunity for idea sharing (Lindblom and Martins, 2022).	HRM1 and HRM3 supported early analytics dashboards streamline meetings while HRM2 confirmed results of HR analytics in HRM.
	Human-AI collaboration design	Offloading routine tasks to algorithms frees cognitive bandwidth and time for exploration	In multiple MNE cases where bots handled routine HR queries letting professionals spend more time on cognitive tasks which is a precursor to innovation (Charlwood and Guenole, 2022).	All the interviews partcipants HRM1, HRM2 and HRM3 confirmed employees had more free time thus can focus on side projects and strategic tasks critical for personal and organisational innovative growth.

Table 4.1: AI-HRM practices and their links

In the Ability domain AI-powered recruitment and development systems contribute to innovation by both improving the quality of human capital and skills acquisition. Tools like algorithmic screening and personalized learning platforms increase access to cognitively diverse talent and allow tailored development paths which in turn raises employees confidence in their capacity to generate novel ideas. For example, personalised upskilling programs were shown to strengthen creative self-efficacy a key component of innovative behaviour.

Second, in the Motivation category AI-based performance management and personalised HR service delivery have been found to support intrinsic motivation and psychological safety which are two vital drivers of employee innovativeness. When algorithmic systems are perceived as fair, transparent and developmental employees generally respond with increased commitment and voluntary efforts. Studies confirm that such systems can support organisational investment in the employee which results in boosting commitment and encouraging experimentation.

Third, in the Opportunity dimension AI facilitates innovation by restructuring the workplace to better support idea generation and knowledge sharing. AI-enabled analytics that map internal expertise networks or automate administrative HR tasks which creates time, access and structural conditions necessary for innovation to emerge. These systems reduce operational friction and help employees collaborate across functional boundaries.

Overall the table's findings highlight that AI does not directly produce innovation rather it enhances the HRM mechanisms that shape employees ability, willingness and freedom to innovate. By targeting these mechanisms in a coordinated and intentional way the organisations can create a workplace that reliably supports individual-level innovation.

Classic HR practices such as training, rewards and participation have an irregular effect on these three AMO pillars. But AI tools help making these practices continuous, personalised and data driven which increases their cumulative effect on innovative outcomes.

We have formulated these individual level innovative outcome practices based on the literature review as seen in chapter 2 and theme table present in Appendix A :

- **Creative cognitive capacity**: Employees produce more and more original ideas.
- **Knowledge sharing behaviour**: Employees actively exchange information across boundaries.
- **Innovative work behaviour (IWB) enactment**: Employees champion and implement ideas.
- **Learning agility and adaptive expertise**: Employees acquire and transfer new skills quickly.

4.1.1. Creative cognitive capacity

Micro learning chatbots as intrinsic motivation supports Intelligent chatbots and virtual assistants allow HRM to nudge employees with context sensitive prompts, feedback and micro learning modules. In Malik et al. (2023) the deployment of AI assistants in a multinational enterprise (MNE) elevated employee experience, satisfaction and commitment which the theories of creativity trace to higher intrinsic motivation and psychological safety which are the core concepts of ideation (Amabile, 1996). Although Malik et al. (2023) did not quantify IWB, the logic is validated by the Bos-Nehles and Veenendaal (2019) study which specifically provides empirical evidence from a quantitative survey of 463 participants from Dutch manufacturing companies linking perceived HR practices (like information sharing and supportive supervision) and the presence of an innovative climate to employees' innovative work behaviour, thus supporting the notion that a supportive HR climate is connected to innovation-related employee outcomes such as idea generation. AI intensifies that support by providing real time, tailored developmental feedback unavailable in traditional HR practice. Similarly the humanised AI interviewer studied by Clavel et al. (2025) modeled socio emotional cues (self disclosure and intimacy) and thereby elevated applicants engagement. The paper studied interview training not onboarding or idea generation directly but their findings support the broader concept that positive AI-mediated exchanges can lead to beneficial employee outcomes (Gong et al., 2025). Organisations that onboard talent via such relational AI interfaces gain newcomers who are more open to voice novel suggestions thus closing the often observed “post hire creativity gap.”

Cognitive Load Reduction
Machine learning analytics deployed on HR datasets can automate routine monitoring and prediction tasks freeing employees attentional resources for exploration. In the study Heidemann et al. (2024) of 680,000 data points from a German federal agency showed that a turnover prediction ML model translated HR data into actionable alerts for line managers which shortens administrative cycles focused on explainability. Subsequent studies observe that relieving supervisory micromanagement encourages subordinates to experiment and learn (Charlwood and Guenole, 2022). Knowledge workers whose performance data are continuously fed back through dashboards can redirect saved time to problem finding and solution prototyping which are the idea generation and idea implementation stages of IWB (Janssen, 2000).

4.1.2. EDI routes in flexible work systems

Renkema et al. (2022) map three “routes” through which public sector employees convert ideas into implemented solutions. It explores how innovation emerges from employees particularly those whose primary tasks do not explicitly require them to innovate. The study identifies specific employee-driven innovation routes through which employees innovate in a formalized business context. It discusses phases of EDI emergence, such as recognizing problems/opportunities (onset), finding solutions (development), communicating ideas, involving others, testing (finalization) and implementing ideas.

AI tools strengthen each route. First, data driven ideation: text mining bots scan citizen feedback and push problem statements to frontline staff.

AI can process large volumes of data, identify patterns and perform data mining (Pereira et al., 2023). AI is used in HR for analytics and can leverage data to guide decisions and understand the workforce (Chowdhury et al., 2023). AI can assist in complex problem-solving, including defining problems and identifying root causes. AI-based systems can also offer insights obtained from analytics (Budhwar et al., 2022). This capability of AI links to it supporting the ideation phase by bringing relevant data and problems to employees’ attention. This could augment employees’ natural ability to recognize challenges from their work routines.

Second, collaborative development: algorithmic project matching recommends complementary skill holders, shortening team formation time.

Pereira et al. (2023) mentions that AI facilitates effective team formation and the importance of forming project teams. AI can assist in matching workers’ skills to tasks. Chowdhury et al. (2023) also highlights the importance of human-AI collaboration and the need for multidisciplinary teams with complementary viewpoints. AI teammates could be involved in complex problem-solving, including evaluating solutions and making plans. It also mentions a Goal Programming Model for Team Formation for Human-Artificial Intelligence Collaboration in the Workplace. The idea that AI could streamline the process of finding and connecting employees with complementary skills for innovation projects aligns well with these capabilities.

Analysing interviews results of participants adds evidence to this route (collaborative development). The interview highlighted that employees are already using Copilot ”to organise workshops and training sessions” and they plan to deploy a chatbot for HR queries an early phase of internal platform innovation (Appendix F). These practices demonstrate how flexible AI supported micro initiatives can bypass formal IT gatekeepers and accelerate experimentation.

Third, experimental implementation: low code AI platforms let non technical employees prototype and test digital services, reducing dependence on IT gatekeepers. In combination, AI HRM expands the opportunity component of IWB models by democratizing access to innovation resources.

Budhwar et al. (2022) discusses the need for employees to acquire new skills like problem-solving, critical thinking and adapting to the digital workplace as well as developing ”AI literacy” and ”fusion skills” to work effectively with AI. AI can potentially free up human time from routine tasks as discussed in the pervious section . The study Malik et al. (2023) also discuss AI enabling autonomy Del Giudice et al. (2023) and the potential for AI tools to assist employees in their work. Redesigning company roles and developing skills to govern human-AI interactions are seen as necessary. Additionally Pereira et al. (2023) supports the idea that AI can change the nature of work and empower employees potentially enabling them to engage in tasks (like prototyping or testing) that were previously restricted to specialists, thereby reducing reliance on traditional gatekeepers like IT. Study by Renkema et al. (2022) notes that project teams enabled the EDI process allowing employees to discuss, test and apply ideas. AI tools could potentially enhance this testing and application phase.

4.1.3. Psychological empowerment and autonomy support

Algorithmic scheduling and task allocation tools often raise concerns about digital Taylorism (Diefenhardt, 2025) which is also known as scientific management which focused on breaking down tasks, measuring performance, standardising processes and exercising control over workers to maximise efficiency and productivity. However, when employees can customise recommender settings or override automatic decisions AI becomes an empowerment lever.

Koch-Bayram and Kaibel (2024) observed that applicants interpret transparent screening algorithms as a signal of organisational openness, indirectly predicting later voice behaviour. Transparency is essential because individuals impacted by AI decisions need to understand how algorithms function before they can trust those decisions (Varma et al., 2023). Understanding the decision-making process and experiencing consistent treatment can reinforce workers beliefs that the organisation values them (Chowdhury et al., 2023). Explanations provided by AI expert systems can help managers understand why a particular decision was made (Vrontis et al., 2022). Gong et al. (2025) even argues for openly and transparently disclosing the utilisation of AI systems. Applicants interpret transparent screening algorithms as a signal of organisational openness which indirectly predicts later voice behaviour which is supported by Jabagi et al. (2025) which indicates that perceptions of procedural fairness which includes transparency and consistency in decision-making are linked to positive outcomes such as perceived organisational support and job satisfaction. Also when decision-making processes are understandable and consistent employees are more likely to trust the system and feel supported. While Koch-Bayram and Kaibel (2024) notes that research hasn’t fully revealed the exact signals organisations send with the use of algorithms in personnel selection it theorises that telling applicants an algorithm is used influences their internal attributions of intent and in turn organisational attractiveness. Additionally, openness and voice behaviour could be linked to a perception of fairness and trustworthiness signalled by transparency.

Langer and König (2023) suggest that explainable AI (XAI) interfaces granting users insight into model logic supports perceived autonomy competence which is a key predictor of intrinsic motivation for creativity (Ryan and Deci, 2000). Explainability is a key component called for to address the opacity of algorithms. For users of algorithm based systems which includes HR managers opacity can undermine adequate trust and hinder insights into decision outputs making it difficult to adequately consider system outputs. While less opacity can foster the utility of systems as decision support tools. For affected individuals such as employees understanding how decisions are made is crucial for evaluating justice and fairness. Opacity can undermine perceived control and autonomy. Thus providing insight into the algorithm's logic through XAI interfaces could directly enhance perceived autonomy competence by making the system's workings understandable and predictable. This aligns with the notion that employees cognitive perceptions of intelligent technologies can influence their appraisal of threats and their reactions (Gong et al., 2025). Increased perceived control and autonomy are linked to job satisfaction and motivation which leads to innovative behaviour (Langer and König, 2023).

4.1.4. Agility through adaptive skill development

Dynamic learning management systems (LMS) driven by recommender engines personalise curriculum in according to performance gaps, career goals and emerging technological trends (Pan and Froese, 2023). Employees exposed to such LMS report higher learning orientation which predicts creativity (Veenendaal, 2015). The following can be drawn from the literature review to show how this works and supports innovation.

AI allows for a shift from generalized HRM practices to more personalised and hyper-personalised through to individualised HRM practices. Hyper-personalisation involves recommending pathways for further skills training and projects based on an employee's profile and interests for future career growth. AI is used for mapping individual preferences and personalization or hyper-personalization of career pathways based on existing insights and preferences. Reinforcement learning algorithms are suitable for monitoring employees content based progress following training. Additionally, a virtual candidate experience chatbot using deep and cognitive learning algorithms will recommend a more personalised training experience based on employee inputs.

With an enhanced skill set employees are more aware of the various alternatives and opportunities and feel more secure in experimenting and trying out new things. By receiving relevant opportunities for training the employees are encouraged to come up with new ideas and to advance. Thus, AI enabled training, development and career opportunities promote the knowledge and specific skills needed for innovation.

Budhwar et al. (2022) also argues that within MNEs AI enabled “skills passports” facilitate micro upskilling aligned with global innovation strategies which results in rapid redeployment of talent into R&D spin offs.

4.1.5. knowledge sharing and boundary spanning

AI HRM reinforces competencies, motivation and opportunity for knowledge exchange which are the C-M-O (can be reframed as the AMO pillars as discussed in table 4.1) triad that predicts collaborative innovation (Naqshbandi et al., 2023).

Competencies

AI HRM contributes to developing the abilities employees need for innovation and effective human-AI collaboration.

AI is used in training and development functions to suggest learning programs connected to work tasks and experience. AI learning programs can foster engagement and lead to innovative learning (Pereira et al., 2023). Intelligent agents such as animated characters can provide real time feedback and support in training and enhancing engagement in web-based learning. Simulations which are defined as AI environments offer interactivity and enhance learning opportunities. AI computer agents can enhance employee skills in strategic and negotiation settings (Vrontis et al., 2022). AI literacy specifically helps human workers collaborate better with algorithm-based systems. The positive effect of human-AI/intelligent technologies configurations is stronger when employees have fusion skills and AI literacy. Also, T-shaped skills involving both in depth knowledge and the ability to apply it across fields are linked to ambidextrous technological innovation by supporting both search depth (for exploitation) and search scope (for exploration) (Budhwar et al., 2022). AI could potentially help identify or foster such skills (Park et al., 2019).

Motivation

AI HRM can influence employee motivation through personalized experiences and potentially by supporting reward systems linked to innovative behaviour.

Personalized HRM approaches enabled by AI offer tailored practices to employee groups which aligns with diverse values and unique attributes. AI allows for personalized considerations and experiences through AI-mediated social interactions which may be challenging in purely human-to-human interactions (Gong et al., 2025). AI-mediated social exchange can lead to positive employee outcomes such as job satisfaction, commitment and reduced intention to quit. Favourable AI-mediated experiences can trigger a norm of reciprocity where employees feel obliged to reciprocate with positive attitudes and behaviours which are beneficial in encouraging innovation (Malik et al., 2022).

Opportunity

AI HRM creates new opportunities for employees to participate in decision-making, collaborate and exchange knowledge and fostering innovation.

Opportunity enhancing HR practices encourage information sharing and participation in decision making. These practices can involve establishing platforms for information sharing and providing opportunities for interaction and collaboration and using knowledge-sharing communities (Naqshbandi et al., 2023). AI-mediated social exchanges represent a mechanism through which employees interact with AI applications for HRM practices which creates a new form of interaction. AI facilitates communications and informal networks thus enriching information flow (Budhwar et al., 2022; Malik et al., 2022).

Additionally, Enterprise social bots mine internal expertise repositories and recommend peers, thereby lowering search costs for cross disciplinary ties. Chowdhury et al. (2023) discusses an AI capability framework in which technical resources (data and algorithms) plus socialisation mechanisms (communities of practice and digital forums) elevate employee knowledge sharing behaviour which is a precursor to both incremental and radical innovations. The diversity present increases combinatory creativity as employees recombine distant knowledge domains into novel concepts (Gong et al., 2025).

4.2. Organisational Level Innovation Outcomes

At the meso and macro levels AI integrated HRM reshapes the organisational context in which ideas are generated, selected and diffused. This section synthesises how AI HRM positively supports and strengthens innovation outcomes such as product development speed, ambidexterity, open innovation success and overall competitive advantage. Below are some of the innovative outcomes that we have categorised.

Strategic Alignment

AI-enabled HR analytics allow organisations to align workforce capabilities with shifting innovation strategies in real time. By mapping skills and availability to ongoing product development or R&D efforts the firms reduce lag between strategic intent and talent execution. AI systems support faster information collection and provide managers with more comprehensive and relevant information for decision making which enhances both efficiency and effectiveness. They can anticipate employees future behaviours by leveraging collected data which can enhance HR practices when recommendations are followed. This capability to predict and align skills coupled with the ability to process vast amounts of data rapidly allows organisations to potentially reduce the lag between strategic intent and talent execution by more quickly identifying and addressing skill gaps or deploying talent. As Marvi et al. (2024) explains this "dynamic capability" approach lets HRM function not only operationally but strategically adjusting human capital configurations as innovation priorities evolve.

Resource Optimisation

Routine HR functions (employee queries, administrative processing) are increasingly automated via AI chatbots and robotic process automation (RPA). This frees financial and cognitive resources that can be reallocated toward innovation driving functions such as cross-functional collaboration or experimentation. From the literature review these are the tasks that employees invest their saved time:

- Strategic decision-making and creativity (Marvi et al. (2024)).
- Participating in practices like the creation of new products (Pereira et al., 2023).
- Innovation-driven organizational changes (Malik et al. (2023)).
- Cognitive tasks, such as evaluating data and analysing implicit information (Varma et al., 2023).
- Complex advisory and problem-solving activities (Malik et al. (2022)).
- Non-trivial tasks requiring expertise and creative intellect (Chowdhury et al., 2023).

Malik et al. (2022) shows that firms that adopted AI bots across HR domains saw measurable cost-effectiveness and greater workforce agility which contributes directly to firm-level innovation capacity. The study presented qualitative case study of a global technology consulting multinational enterprise (MNE) subsidiary in India found that by developing and using HRM-focused AI-enabled applications the MNE improved HR cost-effectiveness and offered hyper-personalised and individualised employee experiences. The study confirmed cost-effectiveness in terms of savings on HR headcount alongside business value-add and HR agility. These AI applications allowed the organisation to deploy resources with greater ease and agility which are gain precursor to innovation.

Dynamic Capability Building

AI-driven learning platforms and talent analytics enable firms to rapidly reskill, redeploy or reconfigure workforce structures which are key requirements for organisational ambidexterity. Marvi et al. (2024) links AI adoption to theoretical perspectives like the Dynamic Capabilities Theory which explains how organizations can adapt, integrate and reconfigure competencies to address rapidly changing environments. AI capabilities can enhance dynamic capabilities which contributes to flexibility and responsiveness. An adaptability oriented perspective for AI in HRM is proposed which suggests a "loose coupling" strategy for flexible adjustment of human resource strategies to adapt to rapidly changing environments. This signifies interconnectivity and swift responsiveness among HRM functions.

Vrontis et al. (2022) notes that AI-HRM systems support "continuous sensing and reconfiguring" allowing organisations to maintain competitiveness through sustained innovation cycles. AI systems can dynamically adapt and remain responsive which is key to maintaining competitiveness. This ability to dynamically manage human capital allows organisations to maintain competitiveness through sustained innovation cycles. The adoption of AI enhances an organization's productivity, knowledge capabilities, creativity and innovation. AI enables organizations to balance exploitation and exploration a balance known as ambidexterity which is crucial for adapting and thriving in the digital age. AI-driven HR analytics supports this by helping bridge skill gaps and developing necessary knowledge, providing the resource base for both exploitation and exploration. This capability is particularly crucial in volatile industries where fast adaptation to technological or market shifts is essential.

Boundary Expansion
AI tools can visualise hidden expertise networks within and beyond organisational silos, supporting open innovation. Lindblom and Martins (2022) shows that when knowledge flows between R&D and sales are formalised via HR facilitated systems where the firms benefit from richer idea recombination and reduced innovation friction. AI-enabled knowledge analytics reduce fragmentation and foster connections that would otherwise remain latent. This helps in managing complex information pools (Gong et al., 2025). AI tools specifically AI-driven HR analytics are noted for their capability to process large volumes of data, identify patterns and generate insights from diverse sources. This ability to make sense of information which includes employee data, skills and competencies and inherently supports the identification and understanding of available knowledge resources within an organization. Again with this ability AI can reveal and leverage dispersed expertise within and across organizational silos. AI can facilitate the sharing and replication of critical knowledge even within complex networks like those found in multinational enterprises.

4.2.1. Talent strategies & innovation goals

Machine learning analytics convert scattered HR data into strategic intelligence (Heidemann et al., 2024). Predictive models of turnover, skill obsolescence and high potential identification allow HR leaders to allocate development budgets to emergent innovation priorities. AI and machine learning (ML) algorithms are powerful tools for converting data into insights and supporting decision making within HRM (Meijerink et al., 2024). ML algorithms offer a way to capture multifaceted relationships in data through inductive research which provides exploratory insights and supports decision making in practice (Heidemann et al., 2024). This method can process large amounts of raw data quickly and efficiently which helps in identifying complicated interactions that humans might miss. AI-driven HR analytics leverages datasets which are often stored in HR Information Systems (HRIS) to redefine how organizations manage their workforce and ensure they have employees with suitable skills and expertise (Chowdhury et al., 2023). AI's capacity to analyze multiple streams of big data supports organizational research and decision making which potentially reduces subjectivity through data mining (Chowdhury et al., 2023). These AI and ML systems are especially beneficial for employee turnover and talent identification.

Malik et al. (2023) describe an AI assisted HRM framework in which algorithmic scenario planning links workforce capabilities to new product roadmaps shortening the planning execution cycle. The paper developed a strategic framework for the adoption of AI technologies in HRM. It reviews the impact of AI-assisted HRM on firm and employee-centric outcomes and frames the findings using human and machine learning frameworks. AI-driven HRM is presented as a new strategic component for firm survival and growth. The framework maps outcomes based on employee experience with AI-assisted HR functions and identifies influencing factors such as nature of human learning competencies, the quality of AI and machine learning methodologies employed and an organisation's orientation and readiness to manage technological change.

Empirical studies on stock building versus flow facilitating HR bundles Sung and Choi (2018) underscore that aligning HR investments with knowledge-flow requirements is critical and AI simply scales that alignment to real time horizons as AI technology contribute to developing organizational knowledge sharing capabilities and enhance productivity by efficiently generating knowledge from various databases (Budhwar et al., 2022). AI tools can uncover implicit knowledge during decision making thus maximizing knowledge sharing and enhancing decision intelligence (Budhwar et al., 2022).

4.2.2. Ambidextrous, radical and incremental innovation

Ambidexterity requires HR configurations for exploitation and exploration to be adjusted. AI driven HR dashboards help micro segmentation of the workforce tailoring incentives and training to each unit's innovation mission (Budhwar et al., 2022).

Park et al. (2019) support the idea that firms need to achieve ambidextrous technological innovation which involves the simultaneous achievement of high levels of both exploratory innovation and exploitative innovation. Andreeva et al. (2017) suggests that different organisational strategies for innovating such as focusing on incremental versus radical innovation may require different HR configurations. Incremental innovation is linked to knowledge recombination and can be supported by certain HR practices while radical innovation requires a search for knowledge outside the firm's domain and may involve greater knowledge ambiguities (Andreeva et al., 2017). As discussed in the section 2.2 we know that AI-enabled tools are capable of offering personalized considerations and experiences through AI-mediated social interactions (Budhwar et al., 2022). Specific AI applications such as talent bots and systems for designing rewards and benefits which are well-suited for delivering personalised solutions particularly in large or geographically dispersed organisations (Malik et al., 2022). AI can also assist in identifying skill-job mismatches and forecasting training needs. These as also discussed is quite critical for supporting ambidextrous innovation.

Park et al. (2019) found that in Korean IT firms high commitment HRM mediated by analytics enhanced HR capability predicted both exploratory and exploitative patent output. While the study did not isolate AI its framework fits with AI enabled "HR capability clusters" that continuously readjust to talent portfolios as innovation horizons shift (Budhwar et al., 2022).

4.2.3. Knowledge management and organisational learning

AI enabled knowledge graphs and recommendation systems codify tacit insights and connect disconnected knowledge domains (Chowdhury et al., 2023). AI can drive knowledge guided innovation and facilitate holistic decision making (Budhwar et al., 2022). Due to the wealth of organisational knowledge resources AI can efficiently facilitate or even replace human decision-making through interactive and integrated knowledge systems and AI tools are capable of uncovering implicit knowledge during decision-making, maximising knowledge sharing and enhancing future decision intelligence (Budhwar et al., 2022). AI-based management practices can enhance knowledge-sharing social interactions. The authors highlight that developing collective intelligence involves a collaborative environment where AI and human intelligence coexist (Chowdhury et al., 2023). They also discuss knowledge management mechanisms as part of enhancing capabilities. AI tools enabling hyper-personalisation and individualisation of

HRM practices have also been noted which could involve providing tailored recommendations based on data.

This supports Budhwar et al. (2022) who describe AI HRM as enabling enterprise wide knowledge sharing via chatbots and digital assistants. Though still in progress these developments suggest potential for long term knowledge recombination and open innovation.

Organisations with such systems realise shorter problem solving cycles and higher reuse of proven components accelerating incremental innovation while freeing resources for exploratory endeavours (Jatobá et al., 2023, Budhwar et al., 2022; Malik et al., 2022). Heidemann et al. (2024) illustrate how explainable predictive models feed lessons learned back into HR policy thus creating double loop learning where both practice and underlying assumptions evolve.

4.2.4. Mitigating innovation risks

Predictive HR analytics can forecast capability gaps and attrition risks innovation process (Heidemann et al., 2024). AI-enabled HR analytics can support strategic HR planning and redefine workforce management to ensure a proficient workforce with the right skills and experience and manage talent (acquisition, development and retention)(Pereira et al., 2023; Budhwar et al., 2022). Predicting attrition allows for developing suitable strategies to retain employees and predicting training needs or identifying skill gaps can create upskilling initiatives (Chowdhury et al., 2023). These capabilities directly address the issues of talent management, skills development and retention that links to innovation and organisational survival (Pereira et al., 2023; Donate et al., 2016). Early warnings allow firms to launch targeted retention or upskilling interventions, protecting critical R&D talent. Budhwar et al. (2022) provide MNE examples where AI HRM dashboards flagged expatriate burnout risk, prompting well being programmes that stabilised global innovation teams.

4.2.5. Diversity driven creativity

AI, particularly in recruitment and selection, offers the ability to access a larger pool of candidates and expand the breadth of searching processes, potentially going beyond documents supplied by candidates to examine online profiles (Pereira et al., 2023). AI is also noted for its potential to reduce bias and be more objective than humans in selection processes (Mirowska and Mesnet, 2022; Budhwar et al., 2022). This reduction in bias alongside the ability to process large amounts of information and access wider data sources could theoretically lead to uncovering underrepresented talent pools (Meijerink et al., 2024; Varma et al., 2023; Charlwood and Guenole, 2022).

Diversity research (Yang and Konrad, 2011; Østergaard et al., 2011) show that heterogeneous teams generate more radical product ideas thus improved innovation capabalities. Algorithmic talent analytics therefore indirectly enhance innovation by increasing cognitive diversity within project teams.

4.2.6. Building dynamic capabilities and strategic agility

Gong et al. (2025) conceptualise four AI HRM pathways one of which is that AI powered innovation (directly using AI to generate new products). This pathway focuses on how the adoption of AI enhances an organisation's productivity, knowledge capabilities, creativity and innovation (Verganti et al., 2020). Organisations can use AI-enabled tools to maintain a balance between exploitation oriented practices and exploration-oriented practices (Gong et al., 2025). Integrating AI capabilities and strategic agility can significantly enhance firms' new product creativity and new service development performance (Gong et al., 2025). Leadership is seen as providing the transformative energy to enable organisations to succeed in AI initiatives which helps members overcome perceived threats and engage constructively with AI (Gong et al., 2025).

Another is AI driven workplace jointly create a dynamic capability which the ability to sense, seize and reconfigure resources for innovation. This pathway involves the growth of AI-based applications influencing HR analytics particularly in reshaping workflow design and revolutionising organisational management practices (Raisch and Krakowski, 2021). The application of AI technology in various HR functions in this pathway which depends on upon specific strategic emphases, including both efficiency orientation AI use aimed at optimising HR processes and minimising costs and effectiveness orientation AI use targeted at elevating the quality and precision of HR decisions to achieve desired outcomes (Gong et al., 2025). AI systems can benefit HR and line managers by improving their decision making efficiency and quality (Gong et al., 2025). Algorithm-based management practices are seen as powerful tools for aligning the interests of managers and employees and improving coordination (Gong et al., 2025). (Pan and Froese, 2023; Pereira et al., 2023) discuss that dynamic capabilities which are sensing, seizing and reconfiguring resources for innovation are enhanced by AI driven HRM.

Sensing

AI driven HRM improves sensing by providing enhanced analytical and predictive capabilities. AI is used in HR analytics to group and interpret employee data for achieving strategic organisational goals (Chowdhury et al., 2023). AI can offer more accurate predictive power for HR decisions. AI-driven HR analytics helps redefine workforce management to ensure the necessary skills, expertise and experience (Malik et al., 2023). This capability to analyse vast amounts of data and identify patterns contributes to sensing changing conditions whether internally regarding the workforce or externally regarding market needs and trends. AI can leverage inter-firm network and employee skills to predict labor market competition (Pan and Froese, 2023).

Seizing

AI driven HRM can improve the ability to seize opportunities particularly those related to talent acquisition and development. AI applications in talent acquisition such as recruitment and selection can process large volumes of data to identify and assess suitable candidates efficiently (Jatobá et al., 2023; Chowdhury et al., 2023; Pereira et al., 2023). The training and development function can employ AI to suggest learning programs connected with work tasks and experience which helps in rapidly developing needed skills within the workforce (Malik et al., 2023). AI can also facilitate effective team formation.

Reconfiguring

AI HRM supports the reconfiguration of resources such as human capital and work processes. AI is used to redesign employee tasks in an efficient and effective manner (Pereira et al., 2023; Malik et al., 2023). It facilitates effective team formation and improves human and machine collaboration (Gong et al., 2025). AI learning programs can foster employees' engagement and lead to innovative learning (Malik et al., 2023). AI can also have applicability in performance management as being used to identify patterns and provide appropriate feedback (Malik et al., 2023). The use of AI-based platforms for career matching supports the idea of facilitating rapid redeployment of talent (Gong et al., 2025).

4.3. Interview Insights

The literature review explored how personalised AI supports employees creativity. Interview with participant HRM1 offers confirmatory evidence by summarizing that "*Some employees are becoming more innovative and proactive in leveraging AI and note more free time after implementation to focus on other projects.*" (Appendix F; section F.1) The extra cognitive free space reported by HRM1 participants aligns with the AMO pathwyas as seen in table 4.1 where offloading routine tasks frees up resources.

Participant HRM1 reported that Copilot now drafts meeting minutes and routine reports helping employees to think ahead rather than type (Appendix F; section F.1). while participant HRM3 noted "*Co-pilot assisting in repetitive tasks is freeing up mental space, reducing stress and workload. This allows employees to focus on more meaningful work*" (Appendix F; section F.3). Participant HRM2 noted "*AI is used to offload mundane, repetitive tasks, saving time and effort. It has helped reduce stress and improve work-life balance.*" (Appendix F; section F.2).

The use of AI for writing emails, preparing documents and organizing meetings as reported by all participants HRM1, HRM2 and HRM3 mirrors findings of Charlwood and Guenole (2022) who observed that automation of low-value tasks enables employees to engage in higher-order thinking and innovation planning which is one of the requiements to enhance innovative capabilities of employees.

Explainability and voluntariness which surfaced repeatedly in the literature as prerequisites for intrinsic motivation (Lin and Sanders, 2017). Interview particpant HRM1 confirms this mechanism by noting that "*AI is seen as augmenting rather than replacing human roles and AI use is encouraged but voluntary*" (Appendix F; section F.1). The absence of mandated usage appears to have fostered "positive energy and openness" (Appendix F; section F.1) which is an emotional state that strongly influences how employees voice their opinions which is again important for innovation (Koch-Bayram and Kaibel, 2024). Participant HRM2 pointed out the importance of AI tools being accessible and user controlled "*Chat GPT and Microsoft Copilot are widely used for daily workflows. Employees appreciate having an approved AI tool leading to positive energy and openness*" (Appendix F; section F.2).

This echoes HRM1's emphasis on AI being "encouraged but not mandated" reinforcing that autonomy over tool usage supports a sense of ownership and psychological empowerment both essential for intrinsic motivation and innovative work behaviour (Deci et al., 1999; Langer and König, 2023).

Participant HRM3 similarly emphasized the need for careful management and support to ensure a smooth transition by noting that "*The organization is planning training programs and AI ambassadors to help employees become comfortable with AI. Managing this transition carefully is key*" (Appendix F; section F.3).

This aligns with the literatures emphasis on explainability and supportive environments as requirements for innovation climates (Koch-Bayram and Kaibel, 2024).

Participant HRM1 highlighted that they took a more practical approach which is company-wide Copilot implementation and tutorials. Though still new and a small step this effort shows that even simple training programs can quickly help employees feel more efficient at handling documents and meetings which is an important step toward developing adaptable skills (Appendix F; section F.1).

Participant HRM2 also observed that AI integration was evolving into a strategic HR function by noting that. *“AI is becoming a part of HR transformation roadmaps. It’s no longer just about automating tasks it’s shifting how we think about skills and roles”* (Appendix F; section F.2). This statement supports the dynamic capabilities framework described by Teece (2018) where learning and sensing capabilities are essential precursors to innovation agility.

Participant HRM3 provided valuable insight into how AI-enabled work environments promote continuous upskilling by noting that “*Development programs aim to help employees become comfortable with AI and integrate it into daily work. We’re planning to train ambassadors to support this shift*” (Appendix F; section F.3).

This also supports the adaptive skill development path outlined in Marvi et al. (2024) where AI-enabled learning ecosystems equip employees for both current tasks and future innovation roles.

In the interview HRM1 mentioned plans to launch an HR service chatbot soon. From the AMO (Ability, Motivation, Opportunity) perspective this would expand the ”opportunity” aspect by making it easier and cheaper for employees to get answers to their questions (Appendix F; section F.1). The chatbot would also store these answers for future use. HRM1 also described a growing sense of “positive energy” (Appendix F; section F.1) across the organization which suggests stronger relationships and trust which are key ingredients for sharing and combining knowledge more effectively. While Participant HRM 2 stated that chatbot are already in use to support employees. Such tools enlarge the ‘Opportunity’ component of the AMO model by making tacit knowledge discoverable which is a prerequisite for cross boundary innovation projects.

Participant HRM1 informed us about one of their future AI integration project which was implementation of a HR chatbot which will work like a simple knowledge graph helping to organize and explain informal policy knowledge (Appendix F; section F.1). This shows their organisation is starting to use AI to capture and share HR expertise which is usually difficult to put into words validating Chowdhury et al. (2023)’s description.

While participant HRM2 mentioned that while AI chatbots are already supporting policy related queries there is a potential to expand this into broader knowledge sharing systems as AI chatbots are used for employee self service such as answering policy-related questions. Participant HRM1 and HRM3 highlighted that in their case no radical product innovations were attributed to AI yet but incremental process innovations are evident such as automated meeting summaries, AI assisted workshop design (Appendix F; section F.1; section F.3). These small steps map onto the exploitative side of ambidexterity freeing resources for later exploratory initiatives.

Participant HRM2 discussed how automation has created cost efficiencies that allow reallocation of resources to innovation efforts as AI helps reduce HR staffing needs by automating certain functions. This means capital can be freed up for innovation related projects (Appendix F; section F.2).

Participant HRM3 noted that AI has helped to reduce workload burdens by stating that “*Employees observed a significant reduction in stress and work-related tensions which allows them to focus on higher impact tasks*”(Appendix F; section F.3). This ties in with Malik et al. (2022) who found that cost-effective AI-driven HR solutions free financial and cognitive bandwidth enabling increased strategic engagement.

Interview with participants HRM1 and HRM3 supports this theorey on how the organization is starting to “seize” opportunities and make some early changes as described in the dynamic capability cycle by (Teece, 2018). By spending less time on routine paperwork which are offloaded to AI which helps employees spend more time on valuable projects the company is slowly reshaping its resources to better prepare for future innovation.

Participant HRM2 noted that AI is now being aligned with strategic HR and innovation goals by stating. *"Organizations are now including AI as a strategic focus in their HR transformation roadmaps"*(Appendix F; section F.2). This demonstrates a tangible application of the strategic alignment as discussed in Gong et al. (2025) where predictive analytics and HR dashboards enable real time workforce planning for innovation needs.

Additionally, participant HRM3 brought up the 70-20-10 learning model to explain how AI could indirectly supports innovation capacity as Employees with better work-life balance and less stress will be more focused on their personal growth and organizational growth enhancing 70% learning on the job." As AI is actively working to offloading repetitive and mundane tasks. This framework strengthens the link between AI-enhanced individual well-being and cumulative organizational innovation outcomes.

Further the interview with participant HRM1 higlighted how HR analytics dashboard is already assisting managers in "identifying focus areas" (Appendix F; section F.1). Although formal metrics are still being developed the quick detection of skill gaps supports Marvi et al. (2024) point that AI-powered tools can speed up how fast strategy is put into action.

Similar observation were also discussed by participant HRM2 as they mentioned *"Organizations are already AI-enhanced modules in HCM (Human Capital Management) systems like SAP SuccessFactors or Workday"* (Appendix F; section F.2) but aslo noted that the integration of these systems is still *fragmented and not fully integrated across HR functions.*

Overall AI driven HR ecosystem allows for a flexible adjustment of human resource strategies to adapt to rapidly changing environments

Based on the results obtained we have developed a framework table as shown in table 4.2 which shows how each of the AI integrated HRM practices contribute to individual and organisational innovative outcomes. This table is a summary of the results which can be used by future research, academia and organisations to see which AI integrated practice leads to which particular innovative outcome or innovative outcome is the result of AI integrated HRM practice.

HRM function	AI integrated HRM Practices	Individual Level Innovative Outcomes	Organizational Level Innovative Outcomes
Recruiting and Selection	Descriptive HR analytics dashboards	- Psychological empowerment & autonomy - Knowledge-sharing & boundary spanning	- Talent and innovation strategic alignment - Resource optimization for innovation - Knowledge-management & org-learning
	Predictive job–talent matching	- Creative cognitive capacity - Psychological empowerment & autonomy	- Talent and innovation strategic alignment - Diversity-driven creativity
	AI sourcing & CV parsing	- Creative cognitive capacity	- Mitigated innovation risks - Diversity-driven creativity
	Video-interview & psychometrics	- Creative cognitive capacity - Psychological empowerment & autonomy	- Diversity-driven creativity
Training and Development	Descriptive HR analytics dashboards	- Psychological empowerment & autonomy - Knowledge-sharing & boundary spanning	- Talent and innovation strategic alignment - Resource optimization for innovation - Knowledge-management & org-learning
	Predictive people-analytics	- Psychological empowerment & autonomy	- Talent and innovation strategic alignment - Mitigated innovation risks - Dynamic capabilities & strategic agility
	Predictive job–talent matching	- Creative cognitive capacity - Psychological empowerment & autonomy	- Talent and innovation strategic alignment - Diversity-driven creativity
	Adaptive learning platforms	- Creative cognitive capacity - Learning agility & adaptive expertise - Innovative Work Behavior (IWB)	- Ambidextrous innovation - Knowledge-management & org-learning - Dynamic capabilities & strategic agility
	Micro-learning chatbots	- Creative cognitive capacity - Psychological empowerment & autonomy - Learning agility & adaptive expertise	- Resource optimization for innovation - Ambidextrous innovation
	HR service chatbots / RPA	- Learning agility & adaptive expertise - Knowledge-sharing & boundary spanning	- Resource optimization for innovation - Boundary expansion / open innovation

HRM function	AI integrated HRM Practices	Individual Level Innovative Outcomes	Organizational Level Innovative Outcomes
Training and Development	Expertise-network analytics	- Knowledge-sharing & boundary spanning - Innovative Work Behaviour (IWB)	- Knowledge-management & org-learning - Boundary expansion / open innovation
	Workforce scenario simulation	- Employee-driven innovation (EDI) routes - Innovative Work Behaviour (IWB)	- Talent and innovation strategic alignment - Ambidextrous innovation - Dynamic capabilities & strategic agility
Performance Management	Descriptive HR analytics dashboards	- Psychological empowerment & autonomy - Knowledge-sharing & boundary spanning	- Talent and innovation strategic alignment - Resource optimization for innovation - Knowledge-management & org-learning
	Predictive people-analytics	- Psychological empowerment & autonomy	- Talent and innovation strategic alignment - Mitigated innovation risks - Dynamic capabilities & strategic agility
	HR service chatbots / RPA	- Learning agility & adaptive expertise - Knowledge-sharing & boundary spanning	- Resource optimization for innovation - Boundary expansion / open innovation
	Expertise-network analytics	- Knowledge-sharing & boundary spanning - Innovative Work Behaviour (IWB)	- Knowledge-management & org-learning - Boundary expansion / open innovation
	Workforce scenario simulation	- Employee-driven innovation (EDI) routes - Innovative Work Behaviour (IWB)	- Talent and innovation strategic alignment - Ambidextrous innovation - Dynamic capabilities & strategic agility
Rewards and Compensation	Descriptive HR analytics dashboards	- Psychological empowerment & autonomy - Knowledge-sharing & boundary spanning	- Talent and innovation strategic alignment - Resource optimization for innovation - Knowledge-management & org-learning
	HR service chatbots / RPA	- Learning agility & adaptive expertise - Knowledge-sharing & boundary spanning	- Resource optimization for innovation - Boundary expansion / open innovation
	Expertise-network analytics	- Knowledge-sharing & boundary spanning - Innovative Work Behaviour (IWB)	- Knowledge-management & org-learning - Boundary expansion / open innovation

Table 4.2: Summarized Table

5 Practical Implications

The findings of this thesis as summarized in table 4.2 carry important practical implications for multiple stakeholders. As AI continues to be integrated into HRM functions both opportunities and challenges emerge for professionals and scholars alike. For HR managers and practitioners the insights from this research provide actionable guidance on how to harness AI technologies to foster individual and organizational innovation.

HR managers are advised to position themselves as innovation facilitators by integrating AI across core HRM functions especially those that impact employee experience such as training, performance management and knowledge sharing. The thesis demonstrates that AI-integrated HR practices such as adaptive learning systems, personalized development plans and transparent performance feedback are critical components for fostering innovative work behaviour.

Among recruitment, performance management, training and rewards AI-integrated training and development emerged as the most influential for innovation. Adaptive learning platforms and microlearning chatbots significantly boost employee creativity, learning agility and idea implementation. HR professionals should prioritize AI-driven learning ecosystems that personalize upskilling, recommend career paths and offer real-time feedback to support exploratory innovation. They can also use other technologies such as skill gap analytics and Virtual/augmented reality simulations to get similar results.

AI tools like CV parsing, video interviews and psychometric analysis support talent acquisition while promoting diversity and reducing bias. This enhances cognitive variety in teams which is linked to more radical and collaborative innovation. HR should use algorithmic tools not just for speed but for hiring which is aligned with their innovation goal by finding candidates with "T-shaped" individuals with both deep expertise and cross functional flexibility.

The results also informed that automating routine tasks such as scheduling and documentation through AI chatbots and Gen AIs such as Microsoft Co-pilot increases employee bandwidth for creative thinking and problem solving. Based on these findings HR professionals should champion integration of AI and Gen AIs in their systems. These AI technologies offload routine and mundane tasks which also frees up time and cognitive capacity which can be reinvested in side projects, cross-functional collaboration and strategic contributions.

HR professionals also can integrate workforce analytics with R&D roadmaps to close the gap between talent supply and strategic needs. AI tools allow real-time mapping of skills, prediction of talent gaps and alignment of HR practices with innovation strategies. This dynamic capability supports ambidextrous innovation which is a key in maintaining the competitive advantage of the organization.

Real-time feedback systems, sentiment analysis from digital communication, Predictive performance and attrition modeling and HR analytics dashboards tools could also be integrated as they support growth oriented feedback, enhance psychological empowerment and flag early signs of disengagement. HR professionals also should ensure to make the feedback loop explainable and supportive not like surveillance which helps in building trust and autonomy. HR professionals can also use AI to identify high potential employees for specific innovation projects.

Interview results also indicated that the way of packaging the AI integration also influences acceptance in the organization. Packaging the AI to suggest time and resource saving saw far more positive acceptance and generally positive enthusiasm in the organization. This highlights how HR managers can potentially package their own AI integrated systems to have a better reception in their organization.

While AI integration is Rewards and compensation is still maturing but the tools can personalize motivation strategies and align incentives with innovation objectives. HR managers and professionals can initiate integration of tools such as AI models for equitable pay benchmarking, Personalized rewards optimization and AI chatbots for transparency. In addition to implementing these tools HR managers should also monitor for equity and bias in AI-generated compensation decisions.

The study also highlights that resistance is lower when AI is presented as a supporting tool rather than replacing human roles. Initiatives like “AI ambassadors” can help bridge technical and cultural gaps. Managers should provide employees with hands-on experience, feedback loops and platforms to voice opinions. This will increase acceptance and drive innovation from the bottom up. Across all AI integrated HRM practices the availability of structured, clean and diverse data is a prerequisite for success.

Many organizations face issues with fragmented datasets, inconsistent data standards or lack of centralized infrastructure which can compromise the reliability of AI systems. In order to mitigate this HR professionals should collaborate with IT and data governance teams to improve HR data pipelines, enforce privacy standards and develop common explanations for roles, skills and performance metrics.

HR managers must be careful during the implementation phase as it may cause transition friction during rollout as manual and digital duplication increases workload. As mentioned above there might be resistance from less digitally literate employees and lack of transparency in AI evaluations can result in this resistance. To mitigate this HR professionals should clearly communicate how performance data is used, adopt explainable AI practices and avoid micro management style feedback systems.

Additional challenges also include over personalization which can isolate learners and reduce collaboration, resistance to “bot led” learning especially when done without human coaching, overreliance on AI may overlook creative potential that’s not visible in data, legal risks around compliance with labor laws and transparency such as GDPR. In order to mitigate these risks HR managers can use phased rollouts and appoint AI “super users” or ambassadors and integrate digital training programs to support transition, combine AI tools with human led learning support and ensure data used to personalize training is diverse, current and inclusive.

6

Limitations and future recommendations

While this study provides valuable insights into the relationship between AI integration in HRM and innovation outcomes it is however not without limitations. These limitations are important to acknowledge as they offer scope for further research.

A key limitation is the scarcity of existing academic literature that directly addresses the intersection of AI integrated HRM and innovation outcomes. While the thesis conducted a rigorous systematic literature review and analysed AI-integrated HR functions and innovative outcomes much of the previous academic work is either conceptual or exploratory. Empirical studies that explicitly and quantitatively link AI-integrated HRM practices to innovation outputs are still limited.

The analysis was primarily guided by the AMO (Ability, Motivation and Opportunity) model and the dynamic capabilities theory. While these frameworks are robust and appropriate for the research context they may not fully capture the ethical, emotional and organizational culture dimensions associated with AI adoption in HR. Concepts such as psychological safety, trust in automation or digital ethics which are acknowledged were not deeply analysed. The use of a broader multi theoretical approach could offer a more generalizable understanding.

Another limitation arises from the evolving nature of AI technologies. Tools and practices that are considered advanced today may become outdated within months. The technological landscape analysed in this research may shift quickly. Which could result in some of the observed patterns to evolve as new capabilities emerge or existing ones become obsolete or commercialized.

This thesis is focused on a systematic literature review with a small number of semi-structured interviews (n = 3) with HR professionals across the high-tech sector. Although the interviews provided meaningful real world validation of the literature findings the small sample size and industry focus limits the empirical results. The perspectives reflect experiences from early adopters in relatively AI-ready industries and may not be representative of broader organizational or cultural contexts such as public sector entities, SMEs or regions with low digital infrastructure.

This research explores theoretical and practical linkages and reveals areas that remain underexplored. The following recommendations are suggested for future research.

The current study is primarily based on a systematic literature review supplemented by three interviews from high tech sectors. Future research should include large scale empirical studies across diverse industries and geographies to validate the conceptual frameworks presented. Cross sector analysis would also help differentiate AI-HRM innovation dynamics in traditional vs. technology intensive organizations.

Innovation outcomes especially at the organizational level evolve over time. Future research should explore how sustained AI integration in HRM affects innovation trajectories over the long term. Future studies could investigate whether early gains in individual creativity and efficiency translate into measurable innovation outputs such as patents, new product launches or market share growth.

While this thesis primarily uses qualitative data and conceptual mapping future studies could focus on developing and applying quantitative metrics for both individual level innovation such as idea generation rates and participation in innovation programs and organizational level innovation such as R&D productivity and open innovation performance. This would allow for stronger causal inferences.

The thesis acknowledges but does not deeply explore the ethical and emotional impacts of AI integrated HRM. Future studies should investigate how explainability, trust, bias and employee sentiment in mediate the AI innovation relationship.

The findings indicate that the success of AI integrated HRM systems depends significantly on how AI is introduced and governed. Future research could examine models of AI governance within HR strategies for fostering digital acceptance and the role of middle management in mediating technological change.

7 Conclusion

This thesis is designed to understand and evaluate the relationship between Artificial Intelligence (AI) integration in Human Resource Management (HRM) and its resulting impact on innovation outcomes. This thesis was motivated by the rise of AI technologies and its increasing integration in industrial functions one of which is HRM and significant lack of research on its impact on innovation. By conducting a comprehensive systematic literature review supported by qualitative interviews with HR professionals across high-tech industries, this thesis aims to bridge that gap and provides a foundational framework to understand how AI-HRM systems affect innovation processes and capabilities.

The central finding of this study is that AI-enabled HRM has a substantial impact on innovation. Its operation can be understood via the AMO (Ability, Motivation and Opportunity) model of HRM. AI tools enhance the ability dimension by enabling more personalized learning and targeted talent matching, they enhance motivation by offering real time feedback, fairness and transparency in evaluations and they enhance opportunity by restructuring workflows and automating mundane tasks freeing up cognitive bandwidth for creativity and exploration.

At the individual level, the findings suggest that AI-integrated HRM systems lead to enhanced cognitive capacity, psychological empowerment and increased engagement in innovative behaviors. Employees using AI-integrated tools, such as personalized learning platforms, AI coaches and automated task assistants demonstrated greater confidence in their abilities and a stronger desire to experiment, share knowledge and contribute creative ideas. This was supported by interview data. Participants in the interview noted that tools like Microsoft Copilot allowed employees to focus more on strategic thinking and side projects by automating repetitive and mundane documentation and scheduling tasks. The use of AI in performance feedback systems promoted a growth mindset and encouraged proactive behavior which are critical precursors to innovative work.

Importantly the study highlighted that AI does not only act as a technological enhancement rather it functions as a supporting tool for human centric innovation (Sung & Choi, 2018). The traditional HRM systems and functions such as LMS (learning management system) and knowledge management and sharing platforms have evolved to become more dynamic, responsive and tailored to the unique needs of employees. This shift allows organizations to support creative capital and cross departmental and cross discipline collaboration which are important components of Innovation at an individual level.

At the organizational level AI integrated HRM systems support several strategic outcomes that are directly tied to innovation. These include stronger alignment between talent strategies and innovation goals, faster deployment of resources, greater agility through dynamic capability building and the facilitation of incremental, radical and ambidextrous innovation. AI-powered analytics allow organizations to predict skill shortages, identify high potential employees and reconfigure teams in real time. Such capabilities help organizations respond more effectively to changing technological and market conditions which helps them to maintain or even enhance their competitive advantage.

AI-driven performance management and workforce planning tools facilitate ambidextrous innovation with the ability to exploit existing capabilities while simultaneously exploring new opportunities. Through HR practices like training, rewards and performance assessments AI enables organizations to pursue dual innovation strategies without compromising on efficiency.This supports the broader argument that AI transforms HRM from a support function into a core strategic asset for innovation management.

Another contributing finding was the role of explainability and transparency in driving psychological empowerment and trust in AI systems. Literature and interviews emphasized that AI must be explainable and used voluntarily to avoid resistance. When AI systems were seen as augmentative rather than controlling as they generated “positive energy” in organizations and led to more experimentation and initiative taking among staff. This further supports the notion that successful AI-HRM integration requires not only technological infrastructure but also cultural readiness and ethical consideration.

Interestingly, the thesis also found that training and development rather than recruitment or performance management showed the most significant impact on innovation. While recruitment was the earliest adopter of AI technologies it was the AI-enhanced learning and development platforms that drove the most realistic gains in innovative outcomes. This underscores the critical role of human and creative capital in innovation processes. Personalized learning, microlearning bots and AI-coached development programs were more effective in creating adaptable, progressive and collaborative workforces.

However, despite these benefits the research also uncovered key challenges and limitations. AI integration is not without risks. Issues such as algorithmic bias, data privacy concerns, lack of transparency and over dependance on automated decision making were frequently cited. These risks can undermine employee trust, reduce psychological safety and hinder the very innovation that AI seeks to enhance. Organizational factors such as data readiness, leadership support and user training emerged as critical components to a successful implementation. Resistance from less tech-savvy employees, limited infrastructure and fragmented HR systems were all noted as obstacles. Another crucial factor was also highlighted during the interview that the acceptance and attitude towards AI integration is largely dependent on how the AI-integrated system is packaged as a whole. If the systems are packaged as time saving tools and technologies they are far more likely to be accepted with a positive outlook.

The interviews also revealed that many organizations are still in the early stages of AI adoption with most initiatives focused on process automation rather than strategic innovation enhancement. This shows that the full potential of AI integrated HRM has yet to be realized in many contexts. However the pathways is quite understandable as organizations that align AI investments with long term innovation goals and foster a human centric approach to AI integration are better positioned to thrive in dynamic and knowledge based environments.

Finally, this thesis provides compelling case that AI-integrated HRM is a powerful tool for innovation when implemented ethically, strategically and thoughtfully. By enhancing the core mechanisms that drive innovative behavior which are ability, motivation and opportunity AI can transform HRM into a vital contributor to both individual and organizational creativity. It requires a balanced approach that acknowledges both the capabilities and the constraints of AI to achieve this potential. Human oversight, ethical design and a supportive culture must go hand-in-hand with technological deployment.

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A

Literature Review Theme Table

Table A.1: Literature Review Theme Table

Paper	**HRM practices**	**Context of study**	**Innovation measure used**	**Ind-level innovation outcomes**	**Org-level innovation outcomes**
Heidemann et al. (2024)	HR analytics / ML to predict turnover, generate explanatory insights	Single organisation case study using archival HR dataset from a German federal agency	no innovation variables measured	Not an innovation construct	Improved HR decision transparency

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Paper	HRM practices	Context of study	Innovation measure used	Ind-level innovation outcomes	Org-level innovation outcome
Malik et al. (2022)	AI integrated chatbots & digital assistants for personalised HR service	Conceptual practitioner article illustrative case of a European MNE	Not applicable	Enhanced employee experience	HR cost effectiveness
Bos-Nehles and Veenendaal (2019)	High-commitment HRM bundle (compensation, T&D, info□sharing, supportive supervision)	Analysis of data from 463 individuals across four manufacturing companies	IWB 11-item scale adapted (Kleysen and Street, 2001; De Jong and Den Hartog, 2010)	Increased Innovative Work Behaviour	Not measured
Renkema et al. (2022)	Training, feedback loops, suggestion platforms, autonomy	explorative single case study of medical laboratory around 40 interviews	Narrative counts of employee driven innovations implemented	Employee Driven Innovation behaviours (qualitative evidence)	Aggregated organisational innovation performance (qualitative inference)
Naqshbandi et al. (2023)	Competency, Motivation, Opportunity enhancing HR bundles	diverse sectors in UK & service SMEs	Self reported inbound open innovation performance scale (number of external ideas adopted)	Higher employee knowledge sharing behaviour	Better inbound open innovation performance

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Paper	HRM practices	Context of study	Innovation measure used	Ind-level innovation outcomes	Org-level innovation outcome
Mellahi and Wilkinson (2010)	Workforce downsizing strategies (speed, motive, magnitude)	downsizing and innovation activities was between 1998 and 2001	Not applicable	Not assessed	Conceptual impact on product innovation
Pan and Froese (2023)	AI tools in recruitment, performance and staffing & selection	comprehensive review of existing academic literature on the intersection of AI and HRM	Not applicable	Conceptual mixed impacts	Conceptual productivity & agility gains
Meijerink et al. (2024)	Platform based talent identification processes	talent identification in tripartite work arrangements in the gig economy	Not applicable	Not addressed	Not addressed
Chowdhury et al. (2023)	AI capability framework	systematic review of multi disciplinary literature	Not applicable	Not addressed	Conceptual link to value creation
Andreeva et al. (2017)	Rewards for knowledge behaviours & performance appraisal alignment	Data from Finnish Funding Agency for Innovation	Self reported counts of radical & incremental product innovations	Not directly examined	Influences radical vs. incremental innovation performance

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Paper	**HRM practices**	**Context of study**	**Innovation measure used**	**Ind-level innovation outcomes**	**Org-level innovation outcome**
Mirowska and Mesnet (2022)	AI based evaluation of asynchronous video interviews in selection	33 participants in France	Not applicable	focus on fairness perceptions	None
Charlwood and Guenole (2022)	Strategic capability building for AI ethics & skills	Conceptual viewpoint article	Not applicable	Conceptual only	Conceptual only
Koch-Bayram and Kaibel (2024)	ML algorithms for applicant screening	342 participants who were potential applicants who were asked to evaluate scenarios involving either algorithmic or human evaluators	Not applicable	None	None
Sung and Choi (2018)	Stock building & flow facilitating HR practices	multi source firm level data over 5 years	New product sales ratio & patent counts	Not measured	Higher firm level innovation
Clavel et al. (2025)	Virtual AI interviewer with social skill features	experimental methodology	Not applicable	None (applicant experience study)	None

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Paper	**HRM practices**	**Context of study**	**Innovation measure used**	**Ind-level innovation outcomes**	**Org-level innovation outcome**
Gong et al. (2025)	AI HRM pathways framework	Systematic literature review	Not directly operationalised	Conceptual review	Conceptual aggregation
Jatobá et al. (2023)	HR strategies for AI adoption	Systematic literature review	Not applicable	Not applicable	Not applicable
Langer and König (2023)	Explainable AI strategies	Conceptual commentary	Not applicable	Not addressed	Conceptual trade offs
Lindblom and Martins (2022)	Cross functional knowledge transfer HR practices	30 interviews of members of the sales and R&D departments	Number of new products & perceived market success	Enhanced knowledge sharing	Improved product innovation performance
Jabagi et al. (2025)	Algorithmic HRM on gig platforms (matching & evaluation)	study targets gig-workers	Not applicable	Not examined (focus on fairness & satisfaction)	Not addressed
Veenendaal (2015)	High involvement HRM bundles	Multi study PhD: surveys of Dutch SMEs & longitudinal panel	IWB scale; firm level new product sales ratio	Higher Innovative Work Behaviour (De Jong & Den Hartog scale)	Improved innovation performance via creative capital
Ko and Ma (2019)	Commitment□based HRM (participatory practices, empowerment)	empirical analysis using time-lagged data from 445 firms	Self reported strength of innovation strategy implementation	Greater employee innovative work practices	Strategic fit & execution of innovation strategy

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Paper	HRM practices	Context of study	Innovation measure used	Ind-level innovation outcomes	Org-level innovation outcome
Park et al. (2019)	High commitment HRM building HR capability	Survey of Korean firms	Counts of exploratory & exploitative patent applications	Enhanced exploration & exploitation skills	Higher ambidextrous technological innovation output
Bornay-Barrachina et al. (2017)	Mutual investment employment relationships	empirical and quantitative of data from spanish firms	New product launches	Greater human & social capital	Higher product innovation capability
Greer and Stevens (2015)	Staffing, development & performance systems for co innovation	Conceptual framework article	Not applicable	Conceptual: improved collaboration skills	Conceptual: better customer driven innovations
Donate et al. (2016)	High profile personal & collaborative HRM	empirical study using quantitative methods with data from spanish firms	Exploratory vs. exploitative innovation capability scales	Personal HRM practices (HPHRMS) mediated by human capital (HC) show a total mediating effect on innovation capabilities (ICap)	Collaborative HRM practices (CHRMS) mediated by social capital (SC) show a partial mediating effect on innovation capabilities (ICap)
Wikhamn et al. (2023)	Inbound, outbound & coupled HRM activities for talent flows	single firm operating in the pharmaceutical industry	innovation projects	More boundary spanning behaviours	Successful open innovation initiatives

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Paper	HRM practices	Context of study	Innovation measure used	Ind-level innovation outcomes	Org-level innovation outcome
Chowhan (2016)	Skill, Motivation & Opportunity enhancing HR bundles	Canadian Workplace and Employee Survey (WES) sample size was 3,154 consisting of data from Canadian workplaces	Binary indicator: introduction of new product/process	Boost to workplace level innovation	Higher organisational performance via innovation
Pan et al. (2022)	AI for employee recruitment	Survey sample of 297 from chinese IT firms	Not applicable	Not addressed	not addressed
Budhwar et al. (2022)	AI based HRM in MNEs	Narrative review article	Not applicable	Enhanced employee experience (conceptual)	Cost effectiveness & decision speed (conceptual)
Vrontis et al. (2022)	Intelligent automation technologies across HR	Systematic literature review of 45 articles	Not applicable	Job redesign & learning opportunities (conceptual)	HRM efficiency & innovation readiness (conceptual)
Malik et al. (2023)	AI assisted HRM across acquisition, development & retention	extended strategic framework for AI-assisted Human Resource Management (HRM)	Not applicable	Better engagement (conceptual)	Higher productivity & advantage (conceptual)

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Paper	**HRM practices**	**Context of study**	**Innovation measure used**	**Ind-level innovation outcomes**	**Org-level innovation outcome**
Varma et al. (2023)	Ethical oversight of AI HR systems	Critical review article	Not applicable	Trust & fairness preserved	Ethical innovation climate
Diefenhardt (2025)	ML based personnel assessment & algorithmic governance	empirical example of HireVue to critically examine its operations	Not applicable	Perceived surveillance & autonomy issues (conceptual)	Data driven selection (conceptual)
Bornay-Barrachina et al. (2012)	Mutual investment employment relationships	150 innovative Spanish firms, involving responses from 300 individuals	Patent counts & new product ratio	Higher human capital investment	Increased patent applications & product innovation
Jiménez-Jiménez and Sanz-Valle (2008)	High involvement HRM (training, job rotation, participation)	analysis of 174 Spanish firms	Composite innovation performance index (product/process)	Enhanced competencies & creativity	Greater organisational innovation & performance
Hong et al. (2019)	Teamwork oriented recruitment, rewards, job rotation	Conceptual review	Not applicable	Higher knowledge sharing (conceptual)	Improved open innovation performance (conceptual)

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Paper	**HRM practices**	**Context of study**	**Innovation measure used**	**Ind-level innovation outcomes**	**Org-level innovation outcome**
Wiblen and Marler (2021)	Automated talent identification systems	study was conducted within a large multi-divisional professional services firm	Not applicable	Not addressed	Governance implications, not innovation
Marvi et al. (2024)	AI enabled knowledge management decision frameworks	502 articles with more than 30,000 cited references	Not applicable	Not examined	Conceptual marketing innovation effectiveness
Seeck and Diehl (2017)	High commitment HRM fostering learning & knowledge sharing	sample of 35 studies	Varies across reviewed studies	Enhanced creativity & IWB synthesised)	Product/process/admin innovation (synthesised)
Meijerink et al. (2024)	Algorithmic decision making & HR analytics	Cross disciplinary narrative review	Not applicable	Trust & fairness perceptions (not innovation)	
Pereira et al. (2023)	AI adoption across HR functions	Systematic review of 60 studies	Not applicable	Conceptual impacts on learning & engagement	Capability building (conceptual)

B
Interview Details

B.1. Interview Protocol

The interview protocol remains the same for all the participants. The interview will begin with the interviewer introducing himself and briefly explaining the purpose of the study. Followed by a brief overview of the interview process including the estimated duration which is about 30 minutes. The interviewer will also describe the interview data management plan which is how the interview will be recorded and transcripts will be stored in TU Delft OneDrive. In case the participants organization does not permit the interview to recorded by the interviewer, the participant will be asked to record the interview and share the recordings and transcripts via e-mail.

We have created a set of 7 questions which navigates through how AI is integrated in HRM to innovation outcomes to challenges and unexpected results obtained from this technology. The questions are not industry specific and are generalised again to have a simpler analysis.

The participants list is based on connections from linkedin. The participants were approached via linkedin with a short description of the project and the purpose of the interview. The participation was completely voluntary and consent form present in appendix E was provided informing them about the project and the data management plan.

Additionally, interview conformation email which was sent to participants conforming their participation is available in Appendix C. After which an email was sent informing them about the informed consent protocol which is informing them about consent form is available in Appendix D.

B.2. Ethics Approval

The Human Research and Ethics Committee (HREC) of TU Delft approved the research and participation was voluntary. The TU Delft data steward verified the data management plan for the thesis. The interviews were conducted via teams and the meetings were recorded and transcripts were stored in TU Delft OneDrive.

B.3. Interview Questions

1. **Can you describe your role in the organizations and your working experience?**

   This question is foundational and serves to establish context. This will help us to understand the participant's position, level of responsibility and familiarity with organizational operations. Background information on the participant's professional role and experience which is essential for interpreting their insights within the appropriate context.

2. **How do you use AI in your organization? Is AI formally integrated into your workflows or do you use it for your personal use (routine use?).**

   This question aims to explore how they use AI in the organization as AI can be used on a personal level such as Gen AI for regular task and is not regulated by the organization and such implementation falls outside the scope of our research as it is not the part of HRM. This question will differentiate the use case of AI and help the interview to be more focused on the regulated AI used in organization specifically AI integrated HRM.

3. **How AI is being used as part of your HRM practices (e.g., recruitment, training, performance management)? Can you give me some examples**.

   This question aims to explore in which particular HRM functions/ practices AI is being currently implemented. This will help us understand where AI is being integrated the most and we can compare the results with the network diagram we created based on the results from literature analysis. This question will also provide insights into use cases which are not covered in the literature.

4. **How each of the AI-driven HR practices that you mentioned before leads to individual level innovative behaviors? Can you give me some examples such as it allows individuals to take initiatives or drive new ideas that were previously unlikely?**

   This question aims to explore the individual innovative outcomes due to AI integrated HRM. This question will help us get real life observations on the benefits of AI integrated HRM some of which might not have been covered by the literature.

5. **How has AI-driven HRM make your organization more innovative?**

   Similar to the previous question this question will help explore the innovative outcomes on an organizational level. Again as the previous question this question might uncover some innovative outcomes which were not theorized by the literature analysis.

6. **Were there any unexpected obstacles that emerged after integrating AI into HR workflows? If so can you please explain them briefly.**

   This question aims to explore the challenges of AI integration in HRM. As exploring the challenges are equally as important as exploring the benefits. This question will help us analyse how the organization behavior hinder the AI integration. Also similar to previous two questions this will also uncover hidden challenges that are not mentioned in the literature.

7. **Finally, If you look back, what would you say has been the most unexpected positive outcome whether at the employee level or the organizational level.**

   This question overall aims to find impact of AI integrated outcomes which would not have been mentioned in the literature or something the organizations also did not expect during their research, planning and implementation.

C

Participant conformation email

Hii Participant,

Thank you so much for accepting my request for an interview. This is the official invite for the interview. The interview will be scheduled soon as per your availability and the duration will be 30-35 minutes.

Here is a summary of the project: This thesis aims to explore the impacts of AI integration in HRM on the innovation on an organisational level and individual level. The thesis will have a multi method approach where we will be conducting an extensive systematic literature review of 43 peer reviewed papers to establish connections between innovative outcomes and AI-HRM after which we will conduct a few interviews to gather insights and perspectives on AI-HRM.

The interview will be recorded for transcription but all your details will be anonymized. You will be sent over a consent form, to clarify all the data related concerns before the interview.

If there are any concerns, please do reach out to me.

Best Regards,

Omkar Ashish Nayak

D

Participant consent request email

Hii Participant,

As we have this interview scheduled for my master thesis research, I am sending over the consent form for the same. The consent form is attached in this mail and you need to sign it and send it back at any time that is convenient for you. This procedure is mandatory for research at TU Delft as this makes sure that the participant is aware of how the data of the interview will be handled.

If there are any other concerns, please feel free to reach out to me.

Best Regards,

Omkar

E

Participant consent Form

You are being invited to participate in a research study titled ”AI integrated Human Resources Management ”. This study is being conducted by Omkar Ashish Nayak, a master’s student at TU Delft, Faculty of Technology, Policy and Management, under the supervision of Dr. Nikos Pachos Fokialis. This research is part of the graduation thesis for the MSc Management of Technology programme.

The Research aims to gain insights about the current AI-enabled HR practices and how they influence innovation outcomes at both the individual and organizational levels. The interview will take approximately 30 minutes to complete.

You will participate in a semi-structured interview focusing on AI applications across core HRM functions—recruitment, learning and development, performance management, and talent retention. Your participation is voluntary, and you may choose not to answer any questions you are uncomfortable with. With your consent, the interview will be recorded and transcribed, after which an anonymous summary will be prepared and shared with you for review. You are welcome to suggest modifications before it becomes publicly accessible as part of the MSc thesis. The collected data may also be reused for future research and educational purposes on technology adoption in energy based sustainable-tech firms, but all outputs will ensure your anonymity. All personal data will be stored on TU Delft’s institutional storage, accessible only to the research team. As with any online activity, there is a minimal risk of data breach, but we will take all necessary precautions to maintain confidentiality. No personal identifiers, such as names or organisations, will be included in the published results. Interview recordings will be securely stored on password protected university servers, and all data will be anonymized during analysis and used solely for academic purposes.

Your participation is entirely voluntary, and you can withdraw at any time. If you choose to withdraw, you may request the removal of your data within a week after the interview.

By participating in the interview, you acknowledge that you have read and understood this information and agree to participate in the study under the conditions stated above.

If you have any questions about this study or your participation, please contact:

Corresponding Researcher:
Name: Omkar Ashish Nayak
E-mail: o.a.nayak@student.tudelft.nl

Date: 09/04/2025

Responsible Researcher:
Name: Dr. Nikos Pachos-Fokialis
E-mail n.pachos-fokialis@tudelft.nl
Date: 10/04/2025

F

Interview Transcript Summaries

F.1. Participant - HRM1

AI Integration in HRM

- Copilot rolled out for everyday use.
- AI used in Recruiting and selection, use of AI CV parsing (used to scan and analyse text and wording of the resume)
- Assisting HR in identifying focus areas.
- Copilot used to increase efficiency of tasks (Enhanced efficiency in meetings).
- Copilot also used to organize workshops and training sessions.
- Chatbots will be integrated next to handle HR related queries.
- AI use training provided for responsible use.
- AI is seen as augmenting rather than replacing human roles which enhances strategic focus by offloading repetitive tasks.
- No mandates AI use is encouraged but voluntary.

Individual level Innovative outcomes

- Enhanced efficiency for employees.
- Efficiency note particularly in routine documentation and meeting processes.
- Some employees are becoming more innovative and proactive in leveraging AI.
- AI used for complex task for employees who think their work more complex than anticipated (details not provided due to confidentiality)
- AI also used for employees who think their job is not as complex as they anticipated (details not provided due to confidentiality)
- Employees noted more free time after implementation of AI to focus on other projects.

Organizational level innovative outcomes

- Not explicitly observed but will benefit from employee level efficiency gains.
- Higher interest in work observed across all employee demographics.

- Employees appreciate having an approved AI tool, leading to positive energy and openness.

Challenges and observations

- More complex roles may undergo significant change due to AI unlike manual roles.
- No significant fear of job loss observed yet though future impacts are anticipated.
- Younger and tech-savvy employees are early adopters.
- Older or less tech-inclined staff show resistance but far lower than anticipated.
- The organization must prepare for changes in required skills due to future automation of high-cognitive-load tasks.

F.2. Participant - HRM2

AI integration in HRM.

- ChatGPT and Microsoft Copilot are widely used by employees for daily workflows which is an informal integration of AI in HRM.
- Organizations are purchasing AI-enhanced modules in HCM (Human Capital Management) systems like SAP SuccessFactors or Workday but this is still fragmented and not fully integrated across HR functions.
- organizations adoption depends on budget and willingness to invest in digital tools.
- Applicant Tracking Systems (ATS) and CV parsing are common.
- AI helps auto-fill data from resumes and assist in the transition from candidate to employee.
- AI automates communication, form filling and stakeholder notifications during performance reviews.
- AI is used to offload mundane, repetitive tasks, saving time and effort
- AI chatbots for employee self-service such as answering policy-related questions.

Individual level Innovative outcomes

- Freeing up employee time and offloading mundane task does lead to lower stress and better worklife balance which leads to better innovative efforts.

Organizational level innovative Outcomes

- AI helps reduce HR staffing needs by automating certain functions thereby reducing capital thus more funds for innovation related projects.
- organizations are now including AI as a strategic focus in their HR transformation roadmaps.
- Increased in efficiency and productivity.

Challenges and observations

- Adoption varies by age and geography. For instance younger employees adapt more easily and organizations in developing countries tend to underinvest in technology.

- A lack of clean and structured datasets is a major hurdle for effective AI deployment.
- Technical teams face errors during configuration, especially during first time implementations.
- Contrary to theoretical literature current usage of AI focused on task automation not sophisticated insights like predicting burnout.
- Resistance is heightened during the transition period where manual and digital systems co-exist creating more work.
- Successful implementation depends as much on human factors as it does on technical readiness.
- Implementation sentiment also depends a lot on how the AI integrated HRM is packaged. If it is packaged as a time and resource saving technology then the organization views it as a far positive experience.

F.3. Participant - HRM3

AI Integration in HRM

- Organisation use Co-pilot for everyday use, but it is in its initial phase.
- Screening and evaluation of resumes by AI is already integrated.
- Copilot is used for managing emails, preparing documents and meeting notes.
- Overall AI adoption is at an early pilot stage with plans to expand use and train ambassadors to support wider adoption.
- Co-pilot is used to offload everyday repetitive tasks.
- AI is also used in job portals and application process to enhance applicant experience.
- AI-powered HR chatbots to assist with common HR queries are not yet in place due to limitations in current HR systems.
- Development programs aim to help employees become comfortable with AI and integrate it into daily work.
- Emphasizes the importance of managing the transition carefully with proper support and training.
- Planned training programs and “super users” or AI ambassadors will support employees in adopting AI tools.

Individual level Innovative outcomes

- Co-pilot assisting in repetitive task freeing up mental space, reducing stress and workload.
- AI even used for writing emails.
- Employees observed significant reduction in stress and work related tensions.
- AI support in managing emails has been a major relief and is expected to reduce mental stress.
- This frees employees to focus on more meaningful work and improves work life balance.
- AI is seen as reducing workload and enabling employees to focus on higher impact tasks.

Organisational level Innovative Outcomes

- In line with the individual level outcomes as employees with free time, better work life balance and less stress will be more focused on their personal growth and organizational growth based on 70-20-10 model. (enhances 70% of the learning on the job, 20% Social learning and 10% formal learning)
- As project is in early stages but they expect increase in capabilities of the organization in terms of innovation.

Challenges and observations

- Obtaining high quality, well structured data sets remains a significant challenge affecting the AI's ability to provide predictive insights.
- The organization still needs to improve employee self-service platforms.
- Extremely optimistic about the AI integration in HRM.